

## **6 ALTERNATIVE WORK SCHEDULES**

Alternative work schedules change the times employees arrive at and leave from the workplace. In essence, they are a demand management technique for spreading the demand for work travel over a longer period of time, or for reducing travel demand by compressing the work week into fewer days. Many U.S. employers have already implemented some form of alternative work schedule; a study performed in the late 1970s found that over 12 percent of private sector businesses with more than 50 employees had alternative work schedule options (Nollen and Martin, 1978).

There are three general types of alternative work schedule programs: staggered work hours, flextime, and compressed work weeks. Staggered hours are staged start work times set by employers which allow different groups of employees to start work at different times. Flextime allows employees to set their own arrival and departure times within company guidelines. For example, all employees may be required to be at work between 9:30 a.m. and 3:30 p.m. but choose any hours which include this time period. Compressed work weeks allow employees to work more hours in fewer days than the usual eight-hour-per-day schedule. One common option is the "4/40" where employees work four 10 hour days per week. Common direct and indirect effects are summarized in Table 6-1.

### **SUMMARY EFFECTS OF ALTERNATIVE WORK SCHEDULES ON TRAVEL**

Staggered work hours and flextime directly affect work travel times. Compressed work weeks reduce VMT and change travel times. Effects are a function of employer policies, the nature of the work force, and the degree to which peak traffic is spread over a long time period prior to implementation of alternative work schedules. This latter issue is important because many urban areas have peak traffic periods occurring from 6:00 a.m. to 10:00 a.m. and 3:00 p.m. to 7:30 p.m. In such areas, alternative work schedules may not produce any noticeable effect on congestion levels.

Direct effects of each of the three alternative work schedule programs are described below.

#### **Staggered Hours**

Studies of staggered work hours in Honolulu and New York have shown this strategy to be effective in changing travel times. One recent evaluation of staggered hours in downtown

TABLE 6-1. Effects of alternative work schedules.

Alternative Work Schedules	
Direct Effects	Indirect Effects
<p><b>Trips:</b></p> <ul style="list-style-type: none"> <li>• For compressed work weeks, work-related trips will decrease proportional to the number of days removed from work schedule (one or two per week).</li> <li>• Flextime, staggered hours and compressed work weeks will produce a trip diurnal profile with a reduced peak and with the peak period spread over a larger time period.</li> </ul> <p><b>VMT:</b></p> <ul style="list-style-type: none"> <li>• For compressed work weeks, work-related VMT will decrease proportional to the number of days removed from work schedule (one or two per week).</li> <li>• Flextime, staggered hours and compressed work weeks will produce a VMT diurnal profile with a reduced peak and with the peak period spread over a larger time period.</li> <li>• Spreading out of the peak period commute will significantly increase speeds and decrease the total commute time.</li> </ul>	<p><b>Trips:</b></p> <ul style="list-style-type: none"> <li>• For flextime and staggered hour schedules, work trip changes will be dependent on whether net mode changes favor carpooling and mass transit. Flexibility can facilitate carpooling and mass transit scheduling or it can hinder matching ridership due to additional need of matching varying work schedules.</li> <li>• Non-work-related trips could increase for compressed week schedules although data is inconclusive. Also, significant changes in non-work profiles (e.g., more vacations) could also occur; however, there is little data to support this.</li> </ul> <p><b>VMT:</b></p> <ul style="list-style-type: none"> <li>• Work-related VMT could change if significant mode changes occur.</li> <li>• Non-work-related VMT could increase for compressed week schedules although data is inconclusive. Also, significant changes in non-work profiles (e.g., more vacations) could also occur; however, there is little data to support this.</li> </ul>

Honolulu found statistically significant reductions in travel time during peak periods. Travel time was measured along specific commute routes. Reductions were up to 18 percent depending on the route (producing a 7 minute saving in the commute) (Giuliano and Golob, 1990). In another experiment in New York involving 220,000 employees, demand was reduced by 25 percent during the afternoon peak 15 minute period (Hines, 1982).

### **Flextime**

Flextime programs have evidenced both changes in solo driving and changes in arrival times. Changes in solo driving are discussed in the section on indirect effects. In a test case in San Francisco at least half of the participants arrived to work 30 or more minutes earlier than before flextime (Jones, 1983). At Bishop Ranch in California, flextime policies also appeared to be successful in shifting employee arrival times to earlier periods (Beroldo, 1990).

### **Compressed Work Week**

A carefully controlled experiment among 7000 federal employees in Denver showed a 15.6 percent reduction in work trip VMT among participants. This is a net effect which considers decreased work trips and weekend non-work trips and increased weekday non-work trips (CSI, 1986). Travel time shifts were also noted; participants arrived one hour earlier on average than before the program, and departed about one hour later. The time of travel change resulted in a 25 percent reduction in peak period arrivals and departures. Of course, the influence of such a shift depends on how many employees participate in the program. In this test case, the participation within federal agencies exposed to the program was 65 percent (Atherton et al., 1982).

### **Indirect Effects**

Employer policies determine the extent to which variable work hours are allowed. Some employers may be more amenable to variable work hour policies than others depending on the type of business. For example, manufacturing and retail enterprises may be well suited to staggered work hours and compressed work weeks but less suited for flextime. To date, several of the successful test cases have been within government agencies. Government and information industries may provide greater opportunities for adoption of variable work hours such as flextime. California's work force has a very high proportion of information workers and thus may be particularly suited to widespread alternative work schedule programs.

Indirect effects primarily act upon non-work trips and mode of travel (for example changes in ridesharing or transit use may result from alternative work hours). The remainder of this section will use the term "new ridesharers and transit users" to refer to individuals who

choose to rideshare or use transit as a result of an alternative work schedule program. Other indirect effects include potential changes in work habits and employee residence locations.

Non-commute trips can be affected by changes in work trips. For example, compressed work weeks may reduce the number of commute trips, but increase non-work trips on days off. Alternatively, three-day weekends available to compressed work week participants may induce more out-of-town travel than would otherwise be the case. Documentation of this subject is limited. However, non-work trip VMT reductions have been noted in some cases such as the Denver experiment (CSI, 1986).

Another indirect effect of variable work hours is on mode of travel for work trips. Potentially a program could encourage or discourage solo driving. A survey of Milwaukee employees who carpooled or used transit asked them to consider a hypothetical flextime program. The survey results implied that 30 to 35 percent would switch to solo driving if the program were implemented (Barton Aschman Assoc., 1981). However, most case studies have shown exactly the opposite result. A number of localities that have implemented alternative work programs have reported increases in ridesharing because of the added flexibility. For example, a Seattle flextime program showed a 10 percent decrease in the number of solo drivers (from 24 percent to 14 percent) (Hines, 1982). Alternatively, employees taking advantage of HOV facilities and alternative modes to bypass congestion may find it easier to drive alone during peak periods as flexible hour programs lessen peak traffic.

Case studies covering specific alternative work schedule programs are discussed below. Their evidence suggests that variable hour programs do affect mode choice, but the results are not consistent. Attempts to review case studies for effects are hampered by the fact that many case studies on alternative work hours do not report mode changes, and some case studies have reported on time periods in which other factors may have been present (for example, case studies in Ottawa and Toronto cited by Jovanis (1981) took place during 1973--a period of unusually high fuel prices).

The Denver study evaluations suggest compressed work weeks had no adverse effects on ridesharing and transit. Another recent study of compressed work weeks suggests it was associated with a decline in solo driving, from 82 percent to 77 percent (Freas and Anderson, 1991).

Flextime and Staggered Work Hours. Some studies show flextime is associated with increased ridesharing, while others do not. A 1982 study concluded, after a detailed statistical analysis of results from several California case studies, that compressed work weeks (including flextime) had positive impacts on ridesharing and transit use (Jovanis, 1981). One recent study of Los Angeles commuters found "staggered shifts were not significantly related to employee mode choice" (Ferguson, 1989). Favorable results from flextime have been documented by RIDES, the regional rideshare agency in the San Francisco Bay Area. RIDES found the placement rate among rideshare applicants on

flextime to be 30 percent compared to 16 percent for applicants not on flextime (Burch, 1988). Further, shared ride and transit use increased by 18 percent and 8 percent, respectively, for employees of Lawrence Berkeley Laboratory participating in a flextime program reviewed in 1981 (Barton Aschman, 1981). However, the city of Pleasanton, California found less favorable results; employee surveys in this suburban city suggest only 7.6 percent of Pleasanton workers under flextime used ridesharing, compared to 11.4 percent of the entire Pleasanton work force (Cervero, 1988).

Other secondary effects on work trips are also possible. For example, employees commuting during a compressed work week may find longer commutes more tolerable, thus increasing per-trip VMT. In the long run, employees might move further from work and incur longer commutes. The case studies reveal nothing on the long-term location and commute decisions of commuters.

## **QUANTITATIVE METHODOLOGY FOR ESTIMATING EFFECTS OF FLEXTIME OR STAGGERED WORK HOURS ON TRAVEL**

Flextime (as well as staggered work hours) requires a somewhat different approach from methodologies for other TCMs because the principal effect is to shift travel times. They have very little effect on trip making; therefore, this discussion focuses on how to estimate the change in the *distribution* of work travel under flextime or staggered work hours. This report focuses on flextime because under a full flextime program, the individual's work hours are a variable, while under a staggered work hours program, the individual's work hours are pre-determined by the employers and thus are in a sense a special case of flextime. Therefore, the methodology focuses on flextime as the more general case. The theoretical methodology presented below may be difficult to follow. A quick understanding can be gained by reviewing the example application presented later in the chapter.

### **Work Trip Timing Effects for Flextime**

Key factors to consider in estimating the effects of a flextime program are

1. Number of employees participating.
2. Number of participating employees that commute to work during peak versus off-peak hours
3. Maximum potential shift in hours of work (e.g., if typical work hours are 8:00 a.m. to 5:00 p.m., is everyone going to choose 7:00 a.m. to 4:00 p.m. or 9:00 a.m. to 6:00 p.m.? Or is the choice between starting as early as 5:00 a.m. or 6:00 a.m. or as late as 11:00 a.m.?
4. Average work trip length for participating employees

5. Average travel time for participating employees
6. Staggered work hours can change travel times significantly. People who used to work 8:00 a.m. to 5:00 p.m. may have the option (or be required) to work 3:00 p.m. to 11:00 p.m. That may also change the timing of non-work trips, which could also change the timing of trips by other household members.
7. Region-specific peak periods (for example, Los Angeles considers the morning peak to be 6:00 a.m. to 10:00 a.m., while other areas consider the morning peak to be 7:00 a.m. to 9:00 a.m.).
8. Added flexibility can give affected employees more opportunities for ridesharing or transit modes. Alternatively, it could break up carpools by causing carpoolers to work at times different from those worked previously.
9. Some people using surface streets may switch to freeways if they begin driving at times when the freeways are not so congested.

Below the analytical steps for estimating the primary effects of alternative work schedules on travel behavior are summarized. These primary effects focus on the work trip changes of program participants; therefore, this methodology does not include an approach for estimating secondary effects of alternative work schedule programs on carpooling and transit use. In the literature review discussed above, the fact that alternative work schedules have had both positive and negative effects on ridesharing was discussed; in some cases carpools are broken up while in others the added flexibility actually encourages ridesharing. The methodology presented below assumes the net effect is small.

The approach for estimating travel activity changes for flextime uses the following steps:

1. Estimate the base case hourly travel distribution
2. Estimate the number of peak work trips affected by flextime
3. Estimate the number of flextime participants that will begin traveling outside the peak period
4. Calculate increases in speeds for flextime program
5. If desired, calculate any induced work and non-work trips using the percent change in speed and elasticity of mode choice or vehicle trip demand with respect to travel time, as detailed in the ridesharing and telecommuting methodologies.

Each of these steps is described more thoroughly in the following pages.

### Estimating the Base Case (i.e., pre-flextime) Hourly Distribution of Travel

Many regions have developed hourly diurnal traffic profiles for use in hourly modeling. These empirical profiles should be used whenever possible in place of the normal distribution presented below.

The purpose of flextime and shifted work schedules is to reduce congestion during peak periods by shifting work travel from peak to off-peak periods. In order to estimate the effects of the program, one must first describe the hourly distribution of travel in the peak periods. One distribution which appears to be a reasonable representation of actual distributions of peak period travel observed in areas such as Honolulu (Giuliano and Golob, 1990) is the normal distribution

$$G(t) = \frac{1}{\sigma\sqrt{2\pi}} \exp^{-1/2\left(\frac{t-\mu}{\sigma}\right)^2}$$

where

$\sigma$  = the standard deviation of the hour when vehicle trips occur, and  
 $\mu$  = the mean hour at which vehicle trips occur.

For the peak morning period, if the starting time is  $t_{\text{start}}$  and the ending time is  $t_{\text{end}}$ , then the mean should be

$$\mu = t_{\text{start}} + (t_{\text{end}} - t_{\text{start}})/2 \quad (6-1)$$

and the standard deviation should be

$$\sigma = (t_{\text{end}} - t_{\text{start}})/2(1.96) \quad (6-2)$$

in order to ensure that 95 percent of all the morning commute trips modeled fall between the times  $t_{\text{start}}$  and  $t_{\text{end}}$ . If there is data available on the actual distribution of these trips, however, the variance and mean should be calculated directly.

Taking the total number of vehicle trips estimated to occur during peak travel periods and applying the above equation to each hour of the peak period, one can estimate the percent of the total vehicle trips that occur during the peak period at each hour by substituting the hour for  $t$ . Multiplying the distribution at hour  $t$  by the number of vehicle trips in the period gives the expected number of vehicle trips at hour  $t$ . The non-work trips also have a distribution of when they occur during the day, and multiplying both the number of work trips and non-

work trips by their distribution functions at hour  $t$  will give the total estimated number of vehicle trips that occur at hour  $t$ . For example, let

$M_{\text{work}}$  = Total work trips made per day

$PW_{\text{pk}}$  = Percent of work trips made during peak periods

$M_{\text{non}}$  = Total number of non-work trips made per day

$PN_{\text{pk}}$  = Percent of non-work trips made during peak periods

$w(t)$  = Distribution of  $M_{\text{work}}$  during peak periods, and

$h(t)$  = Distribution of  $M_{\text{non}}$  during peak periods

Then we have the relationships

$$M = M_{\text{work}} + M_{\text{home}}$$

where

$M$  = total vehicle trips in a region made each day, and

The number of work trips in the morning at hour  $t$  is then:

$$N(t) = \left(\frac{M_{\text{work}}}{2}\right) \frac{1}{\sigma\sqrt{2\pi}} \exp^{-1/2\left(\frac{t-\mu}{\sigma}\right)^2}$$

where

$N(t)$  = number of vehicle trips at hour  $t$  that are work-related.

The total number of peak work trips,  $M_{\text{work}} \times PW_{\text{pk}}$ , has been divided by 2 because it is assumed that half of all peak work trips are made during the morning peak and half during the afternoon peak. The evening commute is calculated similarly. Therefore, one can think of  $w(t)$  as the sum of two such Gaussian distributions,

$$w(t) = \frac{1}{2}G_{\text{morning}}(t) + \frac{1}{2}G_{\text{evening}}(t)$$

where multiplying by one-half splits the number of peak work trips in half for the morning and evening commute periods.



It is important to be aware that the primary effect of alternative work schedules is to shift the distribution of work trips, but not to change their number. Therefore,  $M_{work}$  should be kept constant for the purpose of estimating the primary effects of alternative work schedules.

Total peak period work trip VMT will be approximately equal to the region's average work trip distance multiplied by the number of peak period work trips.

#### Estimate the Number of Peak Work Trips That May Be Affected

The effects of a flextime program on the distribution of work travel depend on two variables: the number of participating employees and the new times they drive. The number of vehicle trips that can potentially be shifted to off-peak hours equals:

$$N_{shift} = \delta \times Y \times PW_{pk}/AVO \quad (6-3)$$

where

$N_{shift}$  = Number of vehicle trips that may be moved to different times due to flextime

$\delta$  = Percent of the work-force in the study region that is participating in the program

AVO = Average vehicle occupancy (this adjusts for trips made in carpools and by transit)

Y = Number of employees in study region making work trips in a vehicle

Note that the relationship between the number of peak work trips and the number of vehicle trips that are work-related is:

$$M_{work} \times PW_{pk} = 2Y/AVO \quad (6-4)$$

#### Estimate the Number of Flextime Participants That Will Begin Traveling Outside the Peak Period

Participants in a flextime program will choose to drive earlier or later than peak periods given the opportunity to do so. For example, suppose prior to the program the morning peak period runs from 7:00 a.m. to 9:00 a.m. and 10,000 work trips occur in this period. Then a flextime program is implemented which allows all participating employees to arrive at work at any time between 6:30 a.m. and 11:30 a.m. If 100 employees who travelled during the peak period participate, the methodology reported here moves 50 of these trips between the hours 6:00 a.m. and 8:00 a.m., and the other 50 between 8:00 a.m. and 11:00 a.m. One

means of redistributing these trips is to create two Gaussian distributions (or, as discussed above, empirical or other distributions) that cover these two morning periods between 6:00 a.m. to 8:00 a.m. and 8:00 a.m. to 11:00 a.m. Other distributions could also be used. For example, the beta distribution, which can be defined in such a way as to concentrate the largest percentage of shifted trips in the periods just before and after the peak periods, could also be used.

The method of creating two Gaussian distributions that shift affected vehicle trips to earlier and later hours than the peak period is discussed next. The following variables are needed:

- $t_{\text{startnew}}$  = Earliest time for participating employees to make trips (i.e., 6:00 a.m. in the example above)
- $t_{\text{endnew}}$  = Latest time for participating employees to make trips (i.e., 11:00 a.m. in the example above).
- $\mu$  = Mean hour of travel of the old peak period (i.e., 8:00 a.m. in the example above)
- $\mu_1$  = Mean hour of travel for the early flex-time travelers
- $\mu_2$  = Mean hour of travel for the late flex-time travelers
- $\sigma_1$  = Standard deviation of the hour of travel for the early flex-time travelers
- $\sigma_2$  = Standard deviation of the hour of travel for the late flex-time travelers.

$\mu_1$ ,  $\mu_2$ ,  $\sigma_1$ , and  $\sigma_2$  are calculated as follows:

$$\begin{aligned}\mu_1 &= (\mu - t_{\text{startnew}})/2 + t_{\text{startnew}} \\ \mu_2 &= (t_{\text{endnew}} - \mu)/2 + \mu \\ \sigma_1 &= (\mu - t_{\text{startnew}})/2(1.96) \\ \sigma_2 &= (\mu_{\text{endnew}} - \mu)/2(1.96)\end{aligned}$$

This yields

$$G_{\text{early}}(t) = \frac{1}{\sigma_1 \sqrt{2\pi}} \exp^{-1/2 \left( \frac{t - \mu_1}{\sigma_1} \right)^2} \quad (6-5)$$

$$G_{\text{late}}(t) = \frac{1}{\sigma_2 \sqrt{2\pi}} \exp^{-1/2 \left( \frac{t - \mu_2}{\sigma_2} \right)^2} \quad (6-6)$$

where

$G_{\text{early}}(t)$  = Distribution of the affected vehicle trips that will occur mostly before the peak, and

$G_{\text{late}}(t)$  = The distribution of the affected vehicle trips that will occur mostly after the peak.

To obtain the number of morning trips that will occur at hour  $t$  after implementation of flex-time, subtract the percentage of affected vehicle trips from the old Gaussian distribution; add 50 percent of the affected vehicle trips times  $G_{\text{early}}(t)$ ; add 50 percent of the affected vehicle trips times  $G_{\text{late}}(t)$ ; and multiply by  $M_{\text{work}}/2$  to get the number of trips. Here is the equation:

$$N(t) = (M_{\text{work}}/2)[G(t) - \delta G(t) + (\delta/2)G_{\text{early}}(t) + (\delta/2)G_{\text{late}}(t)] \quad (6-7)$$

where

$\delta$  = Percentage of vehicle trips affected by flex-time.

Recall that  $M_{\text{work}}$  is divided by 2 because it is assumed that half of all work trips are made in the morning, and the other half are made in the evening. The evening distributions would be calculated similarly.

### Calculate Speed Changes due to Flexitime

There are two speed changes of concern with respect to a flexitime program: the primary change involves those commuters who move their work trip outside the peak period and thus travel at increased speeds; a secondary change involves speed increases during the peak period as a result of reduced traffic congestion (i.e., due to the flexitime commuters who have switched their commute to an off-peak travel time).

Estimate primary speed changes by (1) identifying the differences between peak and off-peak period travel speeds, (2) identifying the number of flexitime participants now travelling in the off peak period (derived from the steps described above), and (3) assuming that off peak period flexitime participants begin travelling at the off-peak period speeds.

Secondary speed changes will probably be too small to observe. However, if there is a need to estimate these changes, calculate the change in speed per roadway by multiplying the percent change in peak period VMT (peak vehicle trips x average trip distance) by the elasticity of speed with respect to volume (see Equation 3-15 of ridesharing).

### Discussion on Potential Increases in Trip Making due to Flextime

As discussed above, the primary effect of flextime is to "flatten" the peak travel periods by shifting travel from the peak to the off-peak periods. The total number of trips  $M$  may change indirectly if decreased congestion results from the travel time shifts. People may choose to make additional non-work trips either during off-peak hours or during hours that were once normally congested, and people who traveled to work by some other mode than single occupant vehicle because of extreme congestion may switch to SOVs. The likelihood of a significant change in trips is partly dependent upon the severity of the initial congested conditions and the magnitude of the change in conditions. For example, congestion is so severe in New York City that driving is a great deal less convenient than taking public transportation; hence, the potential change in trip is likely to be small. The congestion in a city such as Phoenix is not nearly so great as that of New York City, and public transportation services are not as well developed. Hence, the change in trip may be greater. Clearly, the indirect effect of decreased congestion on trips is not only dependent upon the percentage increase in average vehicle speeds, but on other characteristics of the region being modeled. It is likely that the effect of flextime on speeds will tend to be relatively small unless a large proportion of the work force participates in such a program. Thus it may not be necessary to evaluate induced trip making due to increased speeds in the peak period. If the number of participants is large enough, then induced trip making can be estimated in the same way as described for ridesharing and telecommuting; after calculating the speed changes, evaluate the potential for induced trips by multiplying the percent change in travel time by the elasticity of mode choice with respect to travel time.

### **Staggered Work Hours**

A staggered work hour program will encourage some people to drive to work at different hours. Some program participants will change their trips to occur outside the peak travel period, some participants will continue to travel within the peak period, and (perhaps) some small number of participants may be required by their employers to change their travel to the peak period.

To facilitate estimating trip and speed changes, it is important to understand what percent of the program participants will change their trips to occur outside the peak travel period. Estimates will be region-specific; as an example approach of how to estimate the change from peak to off-peak travel, assume that the morning peak period lasts four hours (6:00 to 10:00 a.m.). Also, assume that the number of work trips that occur during this period is evenly distributed (25 percent of peak period work trips occurring in each hour). A staggered hours program that moves trips by one hour will have the following effect: 50 percent of the peak period travellers will continue to travel during the peak period (i.e., those people travelling during the 7:00 to 9:00 a.m. period will move their trip by one hour in either direction, but will still travel during the peak period). Of the remaining 50 percent

(those people originally travelling from 6:00 to 7:00 and from 9:00 to 10:00), half of their staggered hours options will be to move outside the peak period (e.g., 5:00 to 6:00 and 10:00 to 11:00), and half of the options will be to shift into the peak period. Assuming that a staggered hours program is dictated by the employer to meet work demands (rather than a flextime program, which is largely geared to allow employees to travel at their convenience), it is possible to assume that in this example, 25 percent of all work trips will move outside the peak period.

The remainder of this discussion presents a mathematical representation of how to evaluate a staggered hours program.

The most general way to calculate a new distribution in work trips due to staggered work hours is to account for the percentage shift of trips made from hour  $j$  to hour  $k$  for all hours in the day. One would calculate the new distribution of work trips,  $w_{\text{new}}(t)$ , as

$$w_{\text{new}}(t_j) = w(t_j) - p_{jk}w(t_j) \quad (6-8)$$

$$w_{\text{new}}(t_k) = w(t_k) + p_{jk}w(t_j)$$

where

$p_{jk}$  = percentage of trips made at hour  $j$  that move to hour  $k$ , for all hours for which there is a percentage shift,  $p_{jk}$ .

Note that regardless of the distribution used, the functions  $w_{\text{new}}(t)$  and  $w(t)$  must still satisfy the conditions

$$\sum_{i=1,24} [w(t) - w_{\text{new}}(t)] = 0$$

$$\sum_{1,24} w(t) = \sum_{1,24} w_{\text{new}}(t) = 1$$

because the total number of work trips is not being changed, only the time of day they are taken.

The number of trips that will occur at hour  $t_j$  is calculated by multiplying the new distribution in work trips by half the total number of work trips, i.e.,

$$N(t) = M_{\text{work}} w_{\text{new}}(t_j). \quad (6-9)$$

More intuitively, each employer implementing a staggered work hours program will be requiring a certain number of employees to work at start and end times different from those previously worked. A simple application of the methodology would be to perform the following steps:

1. Add up the number of employees whose new start and end times move them from a peak to an off-peak period. Define this variable as  $STG_{pk}$ .
2. Calculate the percent of the total work force represented by these employees as  $PCT_{op}$ .
3. Multiply the number of vehicle work trips taken during peak periods by  $PCT_{op}/AVO$  to get the total number of vehicle trips moved out of the peak period as  $VEH_{op}$ .
4. Calculate the change in VMT during peak periods as the product of the average work trip length and  $VEH_{op}$ .
5. Calculate the change in speeds by multiplying the percent change in VMT by the elasticity of speed with respect to volume.

### Compressed Work Weeks (CWW)

CWWs affect both the temporal distribution of work trips and their number. An example CWW approach is the "4-40" where participating employees work four 10-hour days per week. Another example is a "9/80" program where employees work 80 hours in nine days and get an extra day off every other weekend. On their days off their work trip is eliminated entirely; on their work days their travel times are shifted by two hours. Conceptually, the methodology to estimate CWW effects on travel activities draws from the telecommuting or ridesharing methodologies for trip effects and from the staggered work hours methodology for temporal distribution effects. Since both effects are occurring at the same time, the order in which speed changes are calculated should be altered slightly. The following steps\* can be used to calculate the effects of compressed work weeks on travel activities:

1. Determine the number of participants in the program.
2. Calculate work trip reductions in the same manner as described in ridesharing equation 1. The number of CWW participants is substituted for "CARP" (pay special attention to note regarding previous mode included after Equation 3-1) and the  $P_e$  term is eliminated. In place of the  $F/D$  term, use  $1/5$  (or if evaluating the effects of a "9-80" program, use  $1/10$ ). Offset work trip reductions by potential work trip increases in the same manner as described in ridesharing Equation 4 (with same variable substitutions as noted above).

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\* NOTE: these steps draw from approaches described above but are performed in a slightly different order to properly account for all changes on a daily average basis.

3. Calculate any non-work trip increases in the same manner as ridesharing Equation 6.
4. Calculate the change in peak and off-peak work travel resulting from the different work start and end times necessitated by the compressed work week program. The approach for doing this is similar to that presented for staggered work hours. The total change must be multiplied by 4/5 (for a "4-40" program) to derive a daily average.
5. Calculate the total daily average change in peak period VMT as the sum of
  - A. Daily average work trip reduction x average work trip length x percent of work travel that occurs in the peak period
  - B. Number of trips estimated to move out of the peak period due to time-of-travel changes x average work trip length
6. Calculate changes in speeds using Equation 3-15 from the ridesharing methodology

## **EXAMPLE APPLICATION OF FLEXTIME METHODOLOGY**

Below we present an example of how the methodology for flextime can be applied. Because of the necessity for keeping track of the hourly travel distribution, the example is presented differently from the previous TCMs. The first step is to calculate the old and new hourly travel distributions using:

1. Pre-flexitime peak hour definition (e.g., 7:00 a.m. to 9:00 a.m. in the example)
2. Number of individuals participating in the program (90,041 people in the example)
3. The equation for the normal distribution presented in Chapter 4
4. The potential commute hours allowed under the flexitime program (e.g., 6:00 a.m. to 10:00 a.m.)

### **Definition of Peak Periods and Number of Trips Potentially Affected**

For this example, we assumed that the regular morning peak occurs between 7:00 a.m. and 9:00 a.m. Therefore, the mean hour,  $\mu$ , is 8:00 a.m. and the standard deviation  $\sigma$  is  $(t_{\text{end}} - t_{\text{start}})/2$   $(1.96) = 1.96$ . It is assumed that under the new flexitime program the commuters previously travelling between 7:00 and 9:00 a.m. will now travel between 6:00 and 10:00 a.m.

For the number of individuals participating in the program, the same assumption is made as for the previous applications: 3 percent of the work force, or 90,041 people. To calculate the number of vehicle trips that are potentially affected, one must divide this value by the average vehicle occupancy:

$$N_{\text{shift}} = \delta \times Y \times PW_{\text{pk}} / AVO =$$

$$0.03 \times 3,001,367 \times 0.608 / 1.126 =$$

$$48,619 \quad (6-10)$$

$N_{\text{shift}}$  is the number of trips that can potentially be shifted to off-peak periods,  $\delta$  is the percent of the workforce that is participating in the program;  $Y$  is the number of employees travelling to work in a vehicle (i.e., car or bus);  $PW_{\text{pk}}$  is the percent of work travel that occurs during peak hours. Then a total of 48,619 trips may potentially be shifted by the flextime program.

In order to determine the actual number of trips shifted from the potential number ( $N_{\text{shift}}$ ), a distribution of trips over time, before and after flextime implementation, is needed. For the distribution of peak period work trips prior to flextime implementation, this analysis assumes a standard normal distribution (or Gaussian distribution) based upon the beginning and ending times of the peak period. For the distribution of flextime participants, this analysis assumes two normal distributions on either side of the height of the peak period distribution. These distributions are illustrated in Figure 6-1. In this figure  $S$  and  $E$  represents the start and end time of the peak period prior to flextime implementation where the dashed lines indicate the peak period, and  $S_{\text{Flex}}$  and  $E_{\text{Flex}}$  are the start and end times of the commute for flextime participants. The portion of the flextime curve which extends beyond the dashed lines represents the portion of participants who shift out of the peak period.

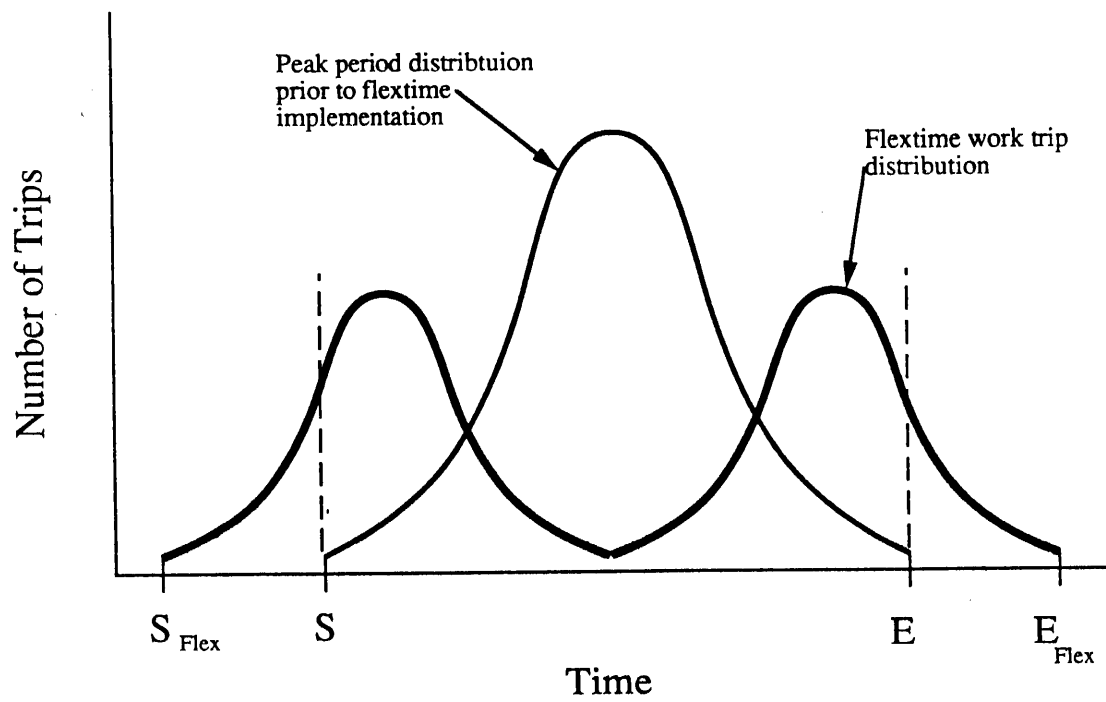
The number of participants traveling during a specific time period can be determined from the equation for the Gaussian distribution:

$$G(t) = \frac{1}{\sigma\sqrt{2\pi}} \exp^{-1/2\left(\frac{t-\mu}{\sigma}\right)^2}$$

where time is given by  $t$ ,  $\mu$  is the mean peak period time (i.e. for a peak period from 7:00 to 9:00, the mean,  $\mu$ , would be 8:00), and  $\sigma$  is the standard deviation which in this analysis we will assume is equal to 1.96 ( $\sigma = 1.96$  indicates that 95% of the distribution is accounted for in the equation; it is statistically unrealistic to have 100% of the distribution accounted for). In our example for the peak period from 7:00 to 9:00, the fraction of trips occurring between 7:00 and 8:00 determined from the equation using  $t=7$  and  $\mu=8$  yields 0.475. This means



FIGURE 6-1. Standard normal distribution curves of the peak period work trips before and after flextime implementation.



that 47.5% of the peak period trips occur between 7:00 and 8:00 corresponding to  $1,620,632 \times 0.475 = 769,800$  trips.

In the methodology, once flextime is implemented, two new distributions are calculated. It is assumed that half of the flextime participants will travel before the mean of the original peak period and half will travel after the mean.  $G_{\text{early}}$  represents those who travel earlier and  $G_{\text{late}}$  is for those who travel later. In our example, if the flextime participants increase their peak period by two hours (one hour earlier and one later), those in the early distribution shift out of the original peak period if their travel occurs before 7:00 and those in the late distribution shift out of the peak period if their travel occurs after 9:00. Using the Gaussian equation and  $\mu_{\text{early}}=8$  and  $\mu_{\text{late}}=9$ , it can be determined that 47.5% of the earlier participants (23.75% of the total) and 47.5% of the later participants (also 23.75% of the total) shift out of the peak period. Thus, the total number of participants who shift out of the peak period is then  $23.75 + 23.75 = 47.5\%$ . This means that out of the 48,619 potential trip shifts there are  $48,619 \times 0.475 = 23,094$  actual trip shifts out of the peak period due to flextime implementation.

It is important to realize that the percent of trip shifts (in this case 47.5%) calculated by this methodology is only a function of two parameters: the original peak period length and the increase in peak period for the flextime participants. Therefore, we present the results of this methodology for several peak periods and increases in peak period lengths for flextime participants. The following table can be used to determine the percent of potential trips shifts which are actual trip shifts. In our example, the original peak period length was 2 hours and the increase in peak period for the flextime participants was two hours (one hour earlier and one hour later).

**Percent of trips removed from peak period by original peak period length and increase in peak period of flextime participants.**

Increase in peak period length for flextime participants	Original peak period length.				
	2 hours	2.5 hours	3 hours	3.5 hours	4 hours
1 hour	23.3%	17.5%	13.9%	11.3%	9.4%
2 hours	47.5%	38.8%	32.3%	27.3%	23.3%
3 hours	62.7%	54.6%	47.5%	41.5%	36.5%
4 hours	71.7%	64.9%	58.5%	52.7%	47.5%

It should be noted that the number of trips moved into earlier and later hours of the peak period is really the most significant difference. This effect will be even more pronounced when the initial peak period is longer than shown here. The primary effect of the flextime program in this methodology is to encourage travel either outside of or in the less-travelled portions of the peak period. This makes intuitive sense: one would expect that the majority of individuals participating in a flextime program do so to try to avoid traffic.

### **Effects of Flextime on Speeds**

If study area data are available for vehicle speeds by hour of the day, then the change in each hour of travel should be used to calculate the change in each hour's speed due to the flextime program. However, most areas simply have peak period and off-peak period speeds. Therefore, the calculation of speed changes is virtually identical to that shown for the previous TCMs.

We assumed that 48,619 peak trips were affected by the flextime program. In the San Francisco Bay Area, 3,653,961 vehicle trips are made per day. 60.8 percent of work trips are made during the peak period, so 2,221,609 vehicle trips are made during the peak period. Therefore  $48,619 / 2,221,609 = 2$  percent of peak period trips are affected by the program. Given that the elasticity of speed with respect to volume is approximately -0.75 during peak hours, a maximum of a 1.6 percent increase in speed can be realized if every flextime participant travels outside the peak period. It is not difficult to see that for a flextime program to have a significant effect, it must affect a much larger proportion of the population.

The next step in the methodology is to calculate the percent change in travel volume during the peak periods which results from implementing the flextime program. After the program is in place, 5,531 trips have moved from the peak to the off-peak periods (2,783 vehicle trips are made at 6:00 a.m., and 2,783 vehicle trips are made at 10:00 a.m., whereas only 17.5 vehicle trips are made during these hours prior to the program). The 5,531 trips translate to a 0.25 percent change in peak travel, and would result in a 0.19 percent increase in speed (assuming an elasticity of -0.75).



## **7 TRAFFIC SIGNAL SYNCHRONIZATION**

Traffic signal synchronization is a traffic engineering approach for reducing high congestion levels. Approximately 30 percent of 1987 VMT was on arterials and local streets in 1987 (ITE, 1989); improving traffic flow on these roadways can significantly increase average speeds. Signal synchronization has been used to improve traffic flow since at least the early 1970s. Typical approaches include installing interconnected pre-timed signals, traffic actuated signals, interconnected actively managed timing plans, and advanced computer controls. Computerized signal systems optimize signal changes through dynamic responses to traffic changes. A summary of potential effects is presented in Table 7-1.

### **SUMMARY EFFECTS OF TRAFFIC SIGNAL SYNCHRONIZATION ON TRAVEL**

Traffic signal synchronization directly affects roadway speeds. Effects may be experienced only along the corridors or regional road networks where synchronization is implemented; or, additional benefits may accrue to nearby roadways as some trips shift to the faster, synchronized roadway. Further, effects are not specific to work or non-work trips; any vehicle travelling on routes with synchronized signals will benefit if congestion is reduced.

#### **Trip Makers**

Traffic signal synchronization can significantly increase vehicle speeds along affected roadways. A 1987 Federal Highway Administration study cited by the Institute for Transportation Engineers (ITE, 1989) noted 8 to 25 percent improvements in speed or travel time by adding advanced computer based controls to systems with varying degrees of timing ranging from none at all to systems with interconnected, pre-timed signals. California's FETSIM (Fuel Efficient Traffic Signal Timing Program) achieved a 15 percent reduction in vehicle stops and delays and an 8.6 percent reduction in fuel consumption (Balog, 1987). A similar program in Florida collected vehicle speeds (before and after) using portable PCs wired into vehicle transmissions. Speed increases of between 15 to 51 percent were documented, depending on the roadway location and time of travel. At certain times of the day on one of the roadways examined, traffic going in the opposite direction of the peak travel experienced 3 percent to 8 percent speed decreases; however, at other times of the day traffic proceeding in the opposite direction experienced increases of 1 percent to 33 percent (Poteat et al., 1987). There may also be effects on cross traffic. For major arterials serving

TABLE 7-1. Effects of traffic signal synchronization.

Traffic Signal Synchronization	
Direct Effects	Indirect Effects
<p>Speed:</p> <ul style="list-style-type: none"> <li>• Traffic signal synchronization will significantly increase vehicle speed along affected roadways and corridors. Speed decreases could occur in opposing directions and for cross traffic.</li> </ul>	<p>Trips:</p> <ul style="list-style-type: none"> <li>• Work and non-work trips could increase due to a net mode change from transit and carpool to single occupant driving if increased vehicle speeds and decreased congestion make single occupant driving more attractive.</li> </ul> <p>VMT:</p> <ul style="list-style-type: none"> <li>• Work and non-work-related VMT could increase due to a net mode change from transit and carpool to single occupant driving.</li> <li>• Work and non-work-related VMT could increase due to route changes designed to utilize the faster roadways and corridors.</li> <li>• Work and non-work VMT per trip could increase if reduced travel time encourages relocation of household further from employment and retail centers.</li> </ul>

highways, such effects may or may not be significant. For synchronization affecting central business districts, cross traffic becomes a constraint on the signal timing that optimizes perpendicular flows.

There is a small probability that signal synchronization will trigger other effects. For example, employees may shift from transit or ridesharing to single occupant vehicles if work route speeds are significantly increased. This shift will depend on where and to what extent signal improvements are made, on their proximity to routes leading to employment centers, and on the extent of perceived speed increases along work routes. Employees may also change travel routes to take advantage of increased speeds. Shifts in routes to and from work may result in either increased or decreased overall VMT depending on whether travel shifts from longer routes taken to avoid congestion or shifts to longer routes to take advantage of reduced congestion along these routes.

Non-work trips are affected in similar ways as work trips. Decreased congestion along pre-existing travel routes may increase non-work trips due to decreased travel time. Additionally, employees may be more inclined to take mid-day non-work trips if congestion is lessened. Shifts in route location may also involve shifts in the location of non-work trips. If speeds are significantly increased along corridors which improve traffic signalization, trip attractors such as retail stores along the affected corridors and routes which access them may experience increased business due to more convenient access to their establishments. Conversely, trip attractors located along routes used as alternatives to streets equipped with synchronized signals may experience decreased traffic.

## **METHODOLOGY FOR ESTIMATING EFFECTS OF TRAFFIC SIGNAL SYNCHRONIZATION ON TRAVEL**

### **Overview**

This discussion presents a methodology to evaluate travel changes from traffic signal synchronization. This measure is included in this report as one example of the many traffic flow improvements that are frequently cited as potential TCMs; other examples of traffic flow improvements include intersection and roadway widening, one-way streets, turn lane installations, and ramp metering (e.g., see Eisinger et al., 1990). Signal synchronization was chosen to represent traffic flow improvements in general due to (1) its popular use throughout California and the rest of the country, and (2) the availability of information discussing the results of signal timing efforts.

To help place signal synchronization in the broader context of traffic flow improvements in general, this discussion is divided into two parts: first, we present a "generic" methodology to evaluate travel changes associated with traffic flow improvements in general; second, we discuss signal synchronization.

## Traffic Flow Improvements

This methodology is a simple approach to viewing traffic flow improvements; it is designed to be simple enough that estimates of improvements can be made with the aid of only a hand calculator. The only data required for the model describing the effects of an increase in capacity is the old vehicle densities, and the length of each link along the road with the new lane. The data required for the example of traffic signal synchronization is an estimate of the percentage decrease in the average number of stops and the percentage increase in the average speeds along each link of the network, the length of each link within the region of retimed lights, and estimates of the number of vehicles that travel each link of the region. The basic model gives travel time savings in terms of (1) idling time and (2) cruising time. Acceleration and deceleration times are not considered, so the data on these times is not required. Hence, the emissions estimates desired from this model's output focus on idling and cruising.

Nearly all traffic flow improvements concentrate on either (1) adding capacity, or (2) completing congestion-relieving improvements that result in smoother, faster-flowing traffic; most of these projects do not directly influence vehicle miles traveled (VMT), but rather attempt to decrease the average travel time (i.e., improve speeds) per vehicle trip. The "generic" traffic flow improvement methodology in this discussion focuses on estimating these speed changes.

A simple representation of the time a person spends driving a vehicle from point A to point B along a road with a new lane considers that (1) the person will be stopped for part of the time, and (2) the person will drive at some mean speed for the rest of the time. The representation of this is:

$$t_{\text{total}} = N_{\text{stop}} t_{\text{stop}} + \sum_{j=1, M-1} D_j / u_j \quad (7-1)$$

where

$N_{\text{stop}}$	=	average number of stops
$t_{\text{stop}}$	=	average time spent at each stop
$D_j$	=	distance between intersections $j$ and $j+1$
$u_j$	=	mean speed between intersections $j$ and $j+1$
$t_{\text{total}}$	=	total travel time
$M$	=	total number of intersections.

Assuming the individual in this example travels at free flow or mostly uncongested conditions, then  $N_{\text{stop}}$  will be very small. If this person travels on city streets, then  $N_{\text{stop}}$  may be large, and  $t_{\text{stop}}$  can increase greatly under gridlock conditions. Similarly, the speed  $u$  is usually substantially greater for a person driving on the freeway than on city streets. The object of most traffic flow improvements is to decrease  $t_{\text{total}}$  by decreasing  $N_{\text{stop}}$ , and/or increasing the speed  $u$ .



We present a sample of traffic flow improvements and show how they affect the equation above. The samples reflect two general types of improvements, those that increase the capacity of a roadway, and those that decrease the total travel time, i.e., by decreasing the number of stops and increasing the mean speed between stops.

### Addition of a Lane

The addition of a lane to an arterial street or a freeway has the effect of increasing the capacity of the road in the direction of flow that acquires the new lane. Increasing the capacity has the direct effect of increasing the average speed of traffic in this direction, and it also has the indirect effect of increasing the number of trips that are made on that road. The increase in trips happens when people choose to travel more on the newly improved road because of the increased speeds.

The percentage increase in capacity for one direction of flow can be represented as:

$$I_{\text{Cap}} = 1/N_{\text{Lane}} \quad (7-2)$$

where

$$\begin{aligned} I_{\text{Cap}} &= \text{percentage increase in capacity} \\ N_{\text{Lane}} &= \text{number of lanes in the direction of flow before the lane was added.} \end{aligned}$$

If the number of vehicles that travel over the road remains the same after the addition of a lane, then the effect of increasing the capacity is to decrease the density of vehicles. The percentage decrease in density is equal to the percentage increase in capacity, and the equation representing this relationship is

$$k_{\text{new}} = (1 - I_{\text{Cap}})k_{\text{old}} \quad (7-3)$$

where

$$\begin{aligned} k_{\text{new}} &= \text{new density} \\ k_{\text{old}} &= \text{old density.} \end{aligned}$$

However, the number of vehicles that pass over the newly widened road will increase because of the attractiveness of the increased average speed. The change in density is better reflected by:

$$k_{\text{new}} = (1 - I_{\text{Cap}} + \epsilon)k_{\text{old}} \quad (7-4)$$

where

$\epsilon$  = percentage of additional vehicles per mile due to latent demand.

$\epsilon$  should be small enough that  $k_{\text{new}} < k_{\text{old}}$ ; the addition of a lane should produce a net decrease in the density of vehicles.

The new speed over the road with the new lane can be estimated using one of two models that relate vehicle densities to expected speeds. One of these models is a linear relationship between vehicle density and vehicle speed, and the other is a log relationship (ITE, 1982). The log model should be used when conditions are congested and traffic densities are near jam density; otherwise, the linear model should be used. For further details on the derivation of these models, see appendix A. The linear model and log model are, respectively,

$$\begin{aligned} u_{\text{new}} &= u_{\text{free}}(1 - k_{\text{new}}/k_{\text{jam}}), \text{ and} \\ u_{\text{new}} &= u_{\text{maxcap}} \ln(k_{\text{jam}}/k_{\text{new}}). \end{aligned} \quad (7-5)$$

The amount of time a person driving along a road with a new lane from point A to point B will save is:

$$\begin{aligned} t_{\text{saved}} &= [N_{\text{stop}} t_{\text{stop}} + \sum_{j=1, M-1} D_j / u_{j, \text{old}}] - [N_{\text{stop}} t_{\text{stop}} + \sum_{j=1, M-1} D_j / u_{j, \text{new}}] \\ &= \sum_{j=1, M-1} \{D_j / u_{j, \text{old}} - D_j / u_{j, \text{new}}\} \end{aligned} \quad (7-6)$$

where

$$\begin{aligned} u_{j, \text{old}} &= \text{the average speed of vehicles between stops before the new lane} \\ u_{j, \text{new}} &= \text{the new speed of vehicles on the road with the new lane.} \end{aligned}$$

Extrapolating from the example described above, a total travel time savings for the region can be estimated by considering all vehicle trips on the road with the new lane. Suppose, as in the example with a single car above, that there are  $M$  intersections along the road with the new lane. Suppose further that the number of vehicles traveling on each segment of the road is known. Then we can calculate an approximate amount of total time saved in the region by:

$$t_{\text{total}} = \sum_{j=1, M-1} N_{j, \text{car}} \{D_j / u_{j, \text{old}} - D_j / u_{j, \text{new}}\} \quad (7-7)$$

where

$$N_{j, \text{car}} = \text{number of vehicles that travel over the new road between intersections } j \text{ and } j+1.$$

In summary, one first calculates the percentage increase in capacity. The percentage increase in capacity is, in this model, equal to the percentage decrease in density, and so the new density of vehicles can then be calculated as the old density times the percentage decrease in density. A correction for latent demand may, at this point, be added to the new density for added precision. Finally, using a model relating the density of vehicles to expected speeds, one can calculate the expected new speed in terms of the new density of vehicles.

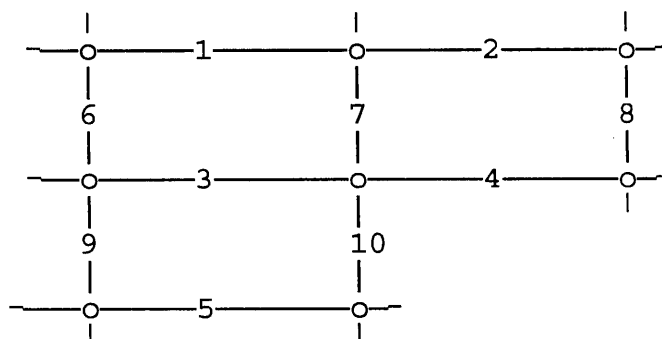
## **Traffic Signal Synchronization**

Traffic signal synchronization will have the effect of decreasing the number of stops vehicles will make, and it will have the effect of increasing the average speed of vehicles over the region where the lights have been synchronized. Computer traffic flow models exist, e.g., TRANSYT 7F (see Skabardonis, 1986; U.S. DOT, 1988), that calculate the cruise time (i.e., total travel time – total delay time), acceleration time, number of stops, deceleration time, and idling time over a network of intersections due to synchronization projects. Given the existence of such tools as TRANSYT-7F, this discussion is geared toward conceptually laying out how a travel impacts analysis should be completed, and how it might be linked to an emissions analysis.

This discussion (1) lays out a simple approach toward evaluating traffic signal synchronization, (2) discusses in more detail how existing models can be used to accomplish these analyses, and (3) illustrates for a model user how to link computer modeling tools to evaluate signal timing to the emission tools necessary to conduct a mobile source emission analysis.

## **Effects of Signal Synchronization**

The implementation of traffic signal synchronization will have the effect of changing the flow of traffic between each signal from all directions. In order to estimate total travel impacts from a timing program, the number of links (i.e., roadway sections between intersections) within the region where the lights are retimed must be known. These will be the sections along which speeds will be increased, and the average number of stops will be decreased. For example, if the geography of a region with eight lights is



then the number of links between the retimed lights is 10. Mathematically, the region and its timing program can be represented using the following variables:

$M$	=	number of links between retimed lights
$t_{\text{stop}}$	=	average time spent at each stop
$u_j$	=	mean speed on link $j$ before the lights are retimed
$N_{\text{stop}}$	=	average number of stops per vehicle before the lights are retimed
$P_{\text{speed}}$	=	percentage increase in speed $u_j$
$P_{\text{stop}}$	=	percentage decrease in average number of stops.

The average speed between intersections  $j$  and  $j+1$ , and the average number of stops after the lights are retimed are then

$$u_{j,\text{new}} = u_j(1 + P_{\text{speed}})$$

$$N_{\text{stop,new}} = N_{\text{stop}}(1 - P_{\text{stop}}).$$

One can calculate an estimate of the average time saved for a vehicle traveling through the region by taking the difference in the time before the lights are retimed and after they are retimed. This difference is represented by the equation

$$t_{\text{saved}} = (1 - P_{\text{stop}})N_{\text{stop}}t_{\text{stop}} + \sum_{j=1,M} D_j / [u_j(1 + P_{\text{speed}})]. \quad (7-8)$$

The total amount of travel time saved (i.e., for all cars) will be

$$t_{\text{saved}}N_{\text{car}}$$

where

$$N_{j,\text{car}} = \text{average number of vehicles traveling over the link } j$$

$$N_{\text{car}} = \text{average number of vehicles traveling through the region of retimed lights } (= \sum_{j=1,M} N_{j,\text{car}}).$$

In summary, speeds will increase on links within a region of lights that are retimed. The number of links and their lengths are inputs to the model. With this information and estimates on the percentage increase in speeds and percentage decrease in the number of stops, one can calculate the expected travel time savings. With additional information about the number of vehicles traveling each link of the network, one can calculate a total travel time savings for the region.

### Analyses Using Existing Modeling Tools: TRANSYT-7F Example

A methodology for estimating emission benefits from signal synchronization has been developed by Skabardonis (1986). The TRANSYT-7F model is run using a variety of input information such as a description of the transportation network, signal timing, link volumes and speeds (U.S. DOT, 1988). From the information produced by the model, total travel time, delay time, total number of stops, and cruise speeds can be determined for each intersection. This information can be used as input to a spreadsheet, along with vehicle emission rates taken from EMFAC7E and other vehicle emission models. The user of this system would be required to calculate the rates of acceleration and deceleration at each intersection from information on intersection geometry and cruise speeds. A spreadsheet can then be designed to calculate overall emissions for a specific intersection timing scenario. Figure 4-1 summarizes the steps required for this procedure.

Following the methodology outlined by Skabardonis (1986), a spreadsheet would be developed to perform the calculations described below. This spreadsheet would require the following information:

Estimates of total travel time, total delay (which includes idling, acceleration, and deceleration), and total stops from the TRANSYT-7F model (seconds);

Cruise and idle emission rates from EMFAC7E (gram/second);

Acceleration and deceleration rates calculated by the user from information on intersection geometry and cruise speed (mph/sec);

Acceleration and deceleration emission rates from either the EPA modal analysis model run for California or obtained from other data sources (gram/second).

From this information, the spreadsheet would need to calculate the amount of time in each emission mode (cruise, idle, acceleration, and deceleration):

$$\text{cruise time} = \text{total travel time} - \text{total delay}$$

$$\text{acceleration time} = (\text{cruise speed}/\text{acceleration rate}) * \text{number of stops}$$

$$\text{deceleration time} = (\text{cruise speed}/\text{deceleration rate}) * \text{number of stops}$$

$$\text{idling time} = \text{total delay} - \text{acceleration time} - \text{deceleration time}$$

The amount of time spent in each emission mode is then multiplied by the appropriate emission rate to obtain total emissions for each emission mode in the network.

## 8 EVALUATING TCM PACKAGES

### INTRODUCTION

This section discusses methodologies to evaluate packages of TCMs rather than individual measures. Most air quality management districts will be implementing TCMs as a package of measures pulled together into a single transportation-air quality management strategy rather than as individual measures acting independently. For most districts, these packages will augment existing and past efforts to implement transportation controls as air pollution and/or traffic congestion relief measures.

TCM packages have been difficult to evaluate because analysts have not been sure how individual measures interact with one another. Two broad thoughts need to be weighed when conducting a TCM packaging analysis: (1) measures overlap target audiences and it is possible to double count the effectiveness of TCMs lacking consideration of this overlap (e.g., one person cannot be both riding the bus and taking a bike to work); similarly, some measures may be effective but may attract participants from other, preexisting programs (e.g., a rideshare participant may switch to transit if transit passes are offered); and (2) the implementation of some measures either improves or diminishes the chances for successful implementation of other TCMs; these "synergies" need to be recognized while analyzing the effectiveness of a given TCM (one example: parking pricing strategies improve the success rate of other programs such as rideshare).

The effectiveness of a package of TCMs is therefore equal to the sum of the effects of individual measures, minus any overlap among measures that target the same audience, plus any "synergistic" effects (positive or negative) resulting from TCM implementation. This is characterized in equation (1).

$$\text{Package} = (\text{Sum of Measures}) - (\text{Overlap}) + (\text{Synergy}) \quad (8-1)$$

The analytical process recommended in this section is designed to (1) simplify the packaging analysis by isolating those TCMs that can be evaluated as individual measures, either because they fail to overlap with other measures or because they will have limited interaction with other measures; and (2) conduct an analysis to estimate overlapping and synergistic responses among the remaining measures. This chapter includes three discussion sections:

- Identifying TCMs to evaluate as individual measures
- Evaluating overlapping and synergistic measures
- Step-by-step directions to apply the methodology

## **IDENTIFYING TCMs TO ANALYZE AS INDIVIDUAL MEASURES**

Some TCMs do not interact with one another and/or do not compete for the same target audience; these measures can be addressed as individual TCMs (i.e., as if they were not part of a package). Several steps can be taken to identify those measures which can be treated as individual measures. First, define the target market for each individual measure in the package, in terms of type of trip targeted (e.g., work trip), type of individual targeted within that trip category (e.g., all service professionals), and the geographic area covered by the TCM (e.g., the central business district (CBD) of a metropolitan area). Second, define which measures overlap. Overlap is a function of the extent to which two or more TCMs target the same group of individuals. For example, a program to build high occupancy vehicle (HOV) lanes might target downtown office workers, with each HOV lane focusing on trips along specific travel corridors. An HOV measure may partially overlap the target audience of a downtown parking management program designed to affect all drivers to a downtown CBD. Nonoverlapping measures can be isolated and analyzed as individual measures.

In addition, to further simplify the analysis, some overlapping measures can be analyzed as individual measures. An individual measure's impacts can be separated and treated individually if the measure either (1) eliminates trips, or (2) substantially shifts the origin or destination (O-D) of trips (i.e., changes the geographic placement of where a trip occurs). The purpose behind separating out these measures is to isolate measures that are not likely to interact synergistically. Measures that eliminate or alter the placement of trips (e.g., telecommuting, land use measures) are not as likely to work in combination with other measures designed to (1) promote alternative travel modes (e.g., such as the use of transit) or (2) alter the timing of when a trip occurs (e.g., such as an alternative work schedule). The remaining, overlapping measures must be evaluated as a package.

## **EVALUATING OVERLAPPING AND SYNERGISTIC MEASURES**

### **Overview: Multi-Attribute Analysis**

Two analytical difficulties must be overcome to estimate the effects of the remaining TCMs in the package: first, for measures targeting the same audience, how can the analyst estimate which measure will be chosen by a given individual or target group? And, second, how can the analyst account for any "synergistic" responses among

measures? The methodology introduced in this section addresses both of these issues through "multi-attribute analysis." The premise of multi-attribute analysis is that it is possible to compare the overall merits of two or more alternatives even though each alternative may have widely differing characteristics and strengths. The methodology depends upon the user's ability to weight the relative importance of each TCM's attributes, and to weight how well individual TCMs compare to one another with respect to any one attribute. Multi-attribute analyses are based on conceptual analytical methodologies described in the decision analysis literature (e.g., see Stokey and Zeckhauser, 1978).

### **Important Attributes to Consider for TCM Analyses**

The foundation to conducting a multi-attribute TCM analysis is a solid understanding of which trip-making attributes individuals consider when deciding how and when to make their vehicle trips. Specific TCMs alter trip making behavior if the measures affect the factors that people consider in deciding upon the nature and frequency of their trip making. To analyze the effects of a package of measures that overlap target audiences, it is important to understand how each measure (both individually and in concert with other measures) affects the key variables that people weigh when deciding upon mode choice.

Individuals directly and indirectly consider numerous attributes of the mode choice opportunities they have when deciding what trips to make and how to make them.

### **Cost and Travel Time**

For most trips, travel time and cost are the two most important factors. As Wachs (1990) states:

Applications of behavioral science to transportation planning give greatest emphasis to travel time and travel cost as the characteristics of travel modes most likely to influence choices made by commuters.

Certain costs are more important than others. Analyses of specific TCMs support the idea that day-to-day costs are the most important cost considerations. Feeney (1989) says that parking costs are weighted more heavily than mileage related or car maintenance costs. Wachs states that "Many studies of commuters' willingness to carpool have shown that commuters consider the out-of-pocket costs of carpooling versus driving alone to be among the two or three most important factors influencing the choice between these modes, the others being travel time and convenience..." (Wachs, 1990).

Similarly, certain time costs are more important than others. "Excess time" (time spent other than just driving enroute) has substantially greater disutility than driving time (e.g.,



some studies show that walking time has twice the disutility of in-vehicle time; Feeney, 1989). Wachs (1990) states that "A variety of studies, conducted in different environments, involving different trip purposes and different modes, have shown that people psychologically weight 'out-of-vehicle time' somewhere between two and three times as heavily as they weight 'line-haul' time or moving time in their travel decisions."

#### Other Attributes Weighed by Trip Makers

Other important variables also determine mode choice. Regarding transit, for example, Wachs (1990) observes that the following variables (listed in order of importance, beginning with most important) determine whether transit is taken: cost, reliability, travel time savings, comfort (climate control, exposure to rain, snow and hot sun), space for packages. Among the range of important considerations identified in other behavioral studies are the following:

**Ridesharing:** There is a strong correlation between commute distance and mode choice; the longer the commute distance is, the higher the ride sharing rates are (Crain, 1984; DOT, 1985). A major deterrent to carpooling is incompatibility of people's schedules. Childcare issues also serve to deter potential ridesharing (people want to be able to respond to emergencies if necessary) (Crain, 1984; DOT, 1984). Part-time carpooling is viewed more positively than regular (i.e., daily) carpooling. In one study, one group expressed a willingness to rideshare on a part-time basis, for example 2 or 3 times per week. The other days they either have specific obligations that require car availability or they simply wish to have their car for the freedom it offers. Some factors considered by people when deciding whether or not to rideshare or take transit involve the other individuals they would travel with; personal characteristics such as smoking can either encourage or discourage potential ridesharers, depending upon their feelings about these habits (Crain, 1984; DOT, 1984).

**Transit Use:** A main transit problem (as cited by SOV commuters) is the length of time necessary to take the bus to work. Surveys reveal a perception that driving takes substantially less time than a transit trip. Another perception is that bus service may be unreliable (Crain, 1984; DOT, 1984). Also, perceived difficulties in deciphering bus and other transit schedules can deter inexperienced transit users from considering transit as a viable alternative to driving (Crain, 1984). Some commuters, especially women, feel that their personal safety is at risk while waiting at, or walking to, bus stops, especially in the dark (Crain, 1984).

**Other Factors Influencing Mode Choice:** Childcare issues can affect commuter mode choice. Many individuals cite the need to respond to child health emergencies and childcare needs as reasons for driving to work rather than taking

transit. Many non-work-related trips during the day are generated by parents shuttling children to daycare, doctors appointments, and other commitments. This trend is more prevalent with women in the work force than men (Crain, 1984; Raux et al., 1986; DOT, 1985). Also, commuters often underestimate or are not aware of their true commute costs; for example, one woman estimated her commute costs, including insurance, gas, maintenance, etc. to be around 4 cents per mile--in actuality, the total cost was around 18 cents per mile.

### Summary of Important Attributes

The major attributes of travel choices can be broken down into four broad categories: (1) cost--including long- and short-term costs; (2) time--including direct travel time enroute plus excess time from the origin and destination to the mode choice; (3) convenience--including comfort, safety, and flexibility of the mode choice; and (4) reliability--focusing on the predictability of the mode choice's ability to reliably deliver the rider to his or her destination.

### **Simplified Example of Applying Multi-Attribute Analysis to TCMs**

TCM packages can be evaluated using multi-attribute analysis by defining how, when packaged with the other measures, each individual measure compares across the four major attributes determining travel characteristics (i.e., cost, time, convenience, and reliability). For example, when two TCMs overlap a common audience, trip makers will choose whether or not to participate in one or another of the TCMs based on each TCM's ability to offer cost, time, convenience, or reliability improvements to the traveller's driving conditions. Figure 8-1 illustrates how a mode choice can be described as a function of these attributes; the figure also describes units of measure for each attribute.

Conceptually, the idea behind a multi-attribute analysis is simply to value each TCM using the attributes of cost, time, convenience, and reliability as a framework for assigning a total value to any one measure. Since each of these four attributes has a different unit of measure (dollars, minutes, etc.), the multi-attribute analysis methodology provides a framework to translate these attributes into common units of measure, and then to sum across the attributes and estimate a total value or "utility" for a given measure. Measures that overlap target audiences can be compared in terms of their total value, and mode choice preferences can be defined. Interestingly, this analytical framework also lends itself directly to consideration of the synergies among measures. For example, assume that SOV users are not participating in a rideshare program (i.e., assume that the total value of SOV use in terms of cost, time, convenience, and reliability is greater than the total value of rideshare). To encourage ridesharing, an employer begins to charge for SOV parking; the employer's parking management program now interacts synergistically with the rideshare program. Using a multi-attribute analysis

Attributes		Units of Measure
Reliability		Percent of time transport is available; predictability of start/end times
Time	Total Travel Time	Minutes or hours
	Total Travel Distance	
Total Mode		Miles
Choice Value	Comfort	Ease of and time to access
	Access to Transport (handicap, walk distance) During Travel (seating, music, companions)	
Convenience	Safety	Aesthetic value
	Flexibility	
Cost	Long-Term (months-years)	Risk of personal injury
	Immediate	
	Weekly-Monthly	Ability to complete other trips/chores.
	Daily	
		Access to immediate transportation
		Range of (and number of options for) start-end times
		Dollars
		Dollars
		Dollars

FIGURE 8-1. Attributes of travel choices.

framework, this synergy can be explicitly captured--the total value of a trip made by SOV now drops relative to the total value of a rideshare trip because the "cost" attribute associated with SOV use is now more expensive. The remainder of this discussion illustrates how a multi-attribute analysis can be used to quantitatively estimate the outcome of implementing multiple TCMs.

Using transit improvements and rideshare programs as a sample set of two TCMs, Figures 8-2 through 8-4 illustrate how a multi-attribute analysis can identify which measures may be preferred among trip makers; the figures walk through the three steps involved with a multi-attribute analysis:

- (1) identifying the "attribute profile" for each TCM by defining each TCM in terms of its cost, time, convenience, and reliability; the attribute profile is an accounting of each attribute for each TCM (e.g., the time associated with an average transit work trip in region "x" is 1 hour);
- (2) creating a "value function" for each measure's attributes by ranking each measure's cost, time, convenience and reliability; the value function helps translate each attribute into similar units of measure so that the attributes can be compared to one another later in the analysis; the value function is represented on a scale from 0 to 1, where 0 equals the worst value an attribute might have, and 1 equals the optimum value an attribute might have; note that this ranking is subjective and is not necessarily a linear function of the absolute value of the attribute in comparison to the best and worst values--the ranking is a reflection of the relative utility of a particular measure's attributes (this concept is explained in greater detail later in the text);
- (3) weighting the relative importance of each attribute (cost, time, convenience, and reliability) in comparison to the other attributes (on a scale from 0 to 1).

Figure 8-2 shows a hypothetical attribute profile for transit and rideshare. The figure indicates that in this example, rideshare is a preferred measure to transit use in every respect except for cost. The figure hypothesizes that for a given trip or trip type, the trip makers experience costs ranging from 14 cents per mile for transit to 20 cents per mile for rideshare, that rideshare is more convenient and takes less time than transit, and that both rideshare and transit are equally reliable.

Figure 8-3 shows a "value function" for each attribute for rideshare and transit. The value function represents the relative utility of the attributes of each measure to a hypothetical trip maker. In the example shown in Figure 8-3, ridesharing takes 1 hour, and transit takes 1.1 hours; the expected range of the trip (from best possible to worst possible) is from 0.75 hours to 1.5 hours. In this example, the utility of a 1-hour rideshare trip is approximately 75 percent of the total utility of the best possible trip--i.e., of a trip lasting only 0.75 hours; the utility of the transit trip (1.1 hours) is only 60

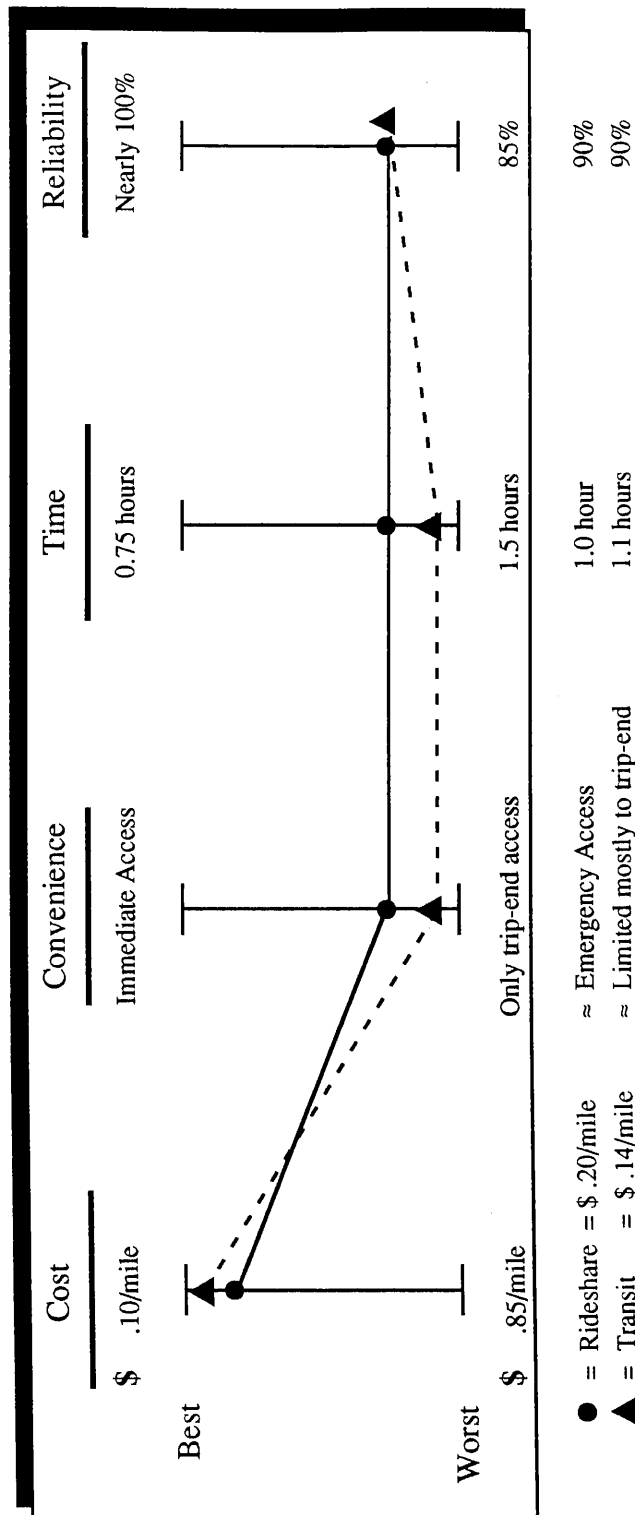


FIGURE 8-2. Sample hypothetical attribute profile for two measures, rideshare and transit.

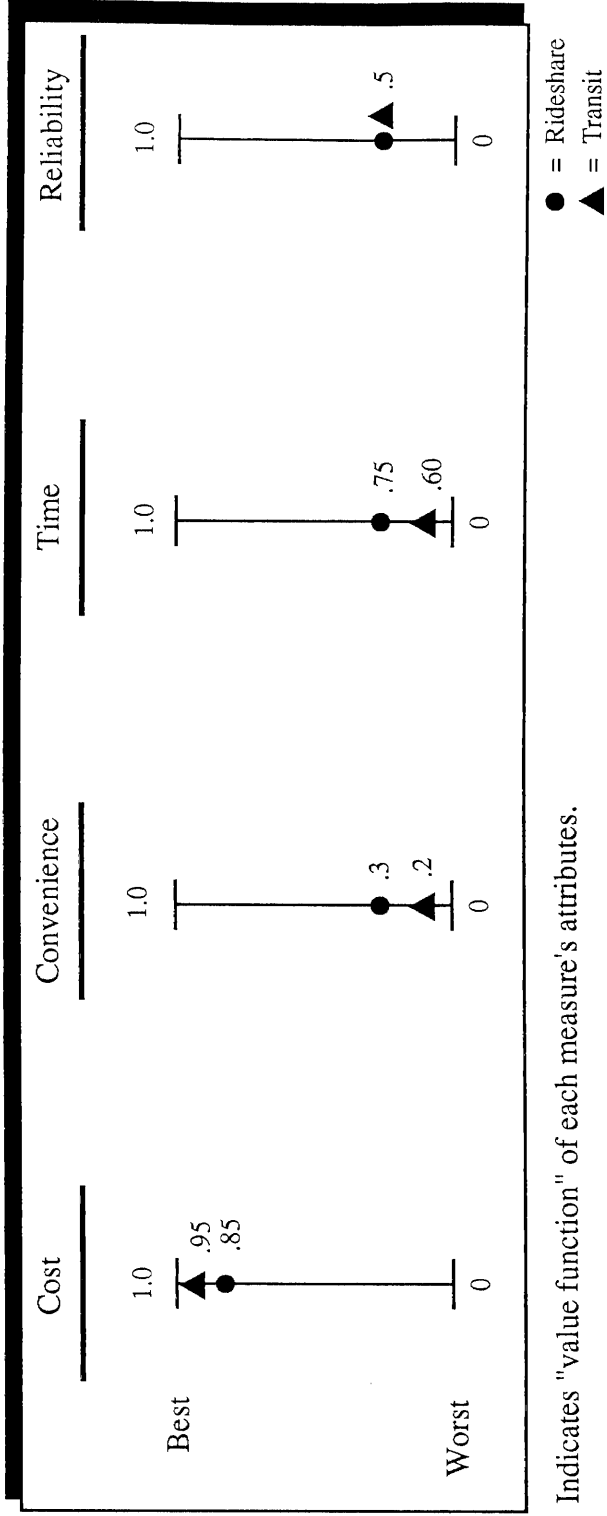


FIGURE 8-3. Value function for each attribute for rideshare and transit.

percent of the optimum trip. Note that these utilities are subjectively defined--they are not necessarily a linear function of the mathematical relationship between a 1 or 1.1 hour trip and the 0.75 hour optimum trip. For example, one would expect that as a trip grows in travel time (or as the "excess time" associated with that trip grows), its utility might drop--perhaps exponentially. For example: 5 additional minutes added to a 10-minute trip might not make that much difference to the trip maker; however, 5 minutes added to a 50-minute trip might represent a significant loss in utility for the trip maker due to the length of the original trip.<sup>1</sup>

Figure 8-4 ties together the attribute profile and the value function for each attribute and illustrates how multi-attribute analysis allows the user to compare two or more TCMs. The overall value, or "total utility," of a particular measure is a function of the value (or utility) of each of its attributes, weighted by how important that attribute is. Figure 8-4 illustrates a potential weighting scheme for cost, time, convenience, and reliability. For example, the bottom box in Figure 8-4 illustrates that cost is four times as important to the trip maker as is reliability, and two times as important as convenience.

In the example illustrated in Figures 8-2 through 8-4, the total utility of the rideshare and transit mode choices depends upon the value function and relative weight of each attribute. Rideshare is shown to be the preferred measure:

$$\begin{array}{rcl}
 \text{rideshare} & = & \frac{\text{cost}}{(0.85 * 0.25)} + \frac{\text{convenience}}{(0.3 * 0.4)} + \frac{\text{time}}{(0.75 * 0.3)} + \frac{\text{reliability}}{(0.5 * 0.05)} \\
 & & = 0.675 \text{ total rideshare utility} \\
 \\ 
 \text{transit} & = & \frac{\text{cost}}{(0.95 * 0.25)} + \frac{\text{convenience}}{(0.2 * 0.4)} + \frac{\text{time}}{(0.6 * 0.3)} + \frac{\text{reliability}}{(0.5 * 0.05)} = \\
 & & 0.65 \text{ total transit utility}
 \end{array}$$

Different weighting schemes would produce a different outcome; for example, trip makers that valued transit's lower cost at a much higher utility than the costs associated with rideshare might prefer transit overall. The weighting schemes clearly depend upon a variety of factors including the type of trip, the income and individual needs of the trip maker, and the quality of the proposed TCM (i.e., value of its attributes).

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<sup>1</sup> Notwithstanding the previous paragraph, we recognize that creating a "value function" is probably the most difficult portion of the entire packaging analysis. The difficulty lies in the subjective nature of trying to assign nonlinear values to a TCM's cost, time, convenience, and reliability attributes. Given these difficulties, it may be appropriate, and it will be easier analytically, to linearly scale the value of a TCM's particular attribute (such as cost), based on its relationship to the "best and worst" value scale for that attribute. This will introduce some error into the analysis, but will still capture the relative ranking by attribute among TCMs. Methodology users will have to experiment and determine which approach best meets their needs given the time they have to conduct their analyses.

## Relating the Multi-Attribute Analysis to TCM Effectiveness

The "total utility" of each measure in a package can be used to gauge the entire package's effects on travel behavior. This can be accomplished by relating the total utility of individual measures to the travel behavior of the target audience.

This discussion provides a mathematical representation of how to estimate the percent of time the target audience utilizes the individual measures within a TCM package. Suppose there are  $N$  different modes of travel that are being considered to be part of the TCM package (for example,  $N$  might be 3, representing transit, rideshare, and telecommuting). For each person, there is a set of values  $TU_k$  for  $k = 1$  through  $N$ , where  $TU_k$  represents the total utility of TCM "k." The percentage of time that a person will travel using mode  $k$  will depend upon the TU of  $k$  in relation to the TU of their remaining mode choice options. For example, if a person has a total mode utility value of 0.9 for single occupant travel and only 0.1 for public transit, then it is unlikely that this person will travel on public transit (given two options, people will almost never buy a product of clearly inferior value.) However, if a person has a TU of 0.41 for single occupant travel and 0.40 for public transit, then it is probable that this person will take public transit nearly the same amount of time he or she rides in a single occupant vehicle. In precise terms, the packaging methodology must consider that the percentage of time a person will travel via mode  $k$  is dependent upon the differences in magnitude between  $TU_k$  and all the other TU numbers for that person.

When extending a TCM's total utility to an entire target market of trip makers, the total utility serves as a surrogate for the degree to which a specific measure will be utilized. To relate total utility to percent of time a TCM is utilized, it is important to represent that measures of little value are not likely to be utilized, while measures of greater value are likely to be substantially utilized. As a concrete example, consider one of the packages just discussed: a person has a total mode utility value of 0.9 for single occupant travel and only 0.1 for public transit. With such a large disparity in utility between these two travel options, it is unlikely that transit will be utilized. It is therefore inappropriate to linearly relate target market for a TCM to its total utility (i.e., in this example, it is unlikely that 10 percent of the target market would utilize transit). A better mathematical approach relating total utility to target market use of a TCM is to relate the percent of time that the target audience will utilize a given TCM as a function of the square of the utility of that mode choice. Mathematically, using the square of the utility accentuates the differences between measures that have widely different utilities, while maintaining a closer balance between measures that have similar utilities. Note that the methodology poses this mathematical relationship as a model to estimate travel behavior; the model is not based on observed empirical evidence.

Equation 8-2 illustrates how to estimate percentages of mode travel for a person with TU values  $TU_1$  through  $TU_N$ , using the mathematical model just discussed:



$$P_k = \frac{TU_k^2}{(\sum_{j=1,N} TU_j^2)} \quad (8-2)$$

where  $P_k$  = percentage of time this person (or target group of trip makers) will travel via mode k.

We can illustrate how to use Equation 8-2 by continuing with the transit and rideshare example included in Figures 8-2 through 8-4. As estimated earlier, the total utility of rideshare was 0.675, and the total utility of transit was 0.65. Based on Equation 2, the percent of time the target audience would rideshare as compared to using transit is equal to:

$$\begin{array}{l} \text{percent of time} \\ \text{a target audience} \\ \text{would choose rideshare} \\ \text{versus transit} \end{array} = \frac{(0.675)^2}{[(0.675)^2 + (0.65)^2]} = 52\%$$

Note that this example does not include consideration of existing travel modes; if the analytical objective were to evaluate the percent of ridesharers and transit users in comparison to SOV travellers, the analysis would also need to include a total utility value for SOV use. When a complete analysis of TCM market share versus existing travel modes is conducted, the analysis will need to be organized so that it captures all of the travel modes under consideration by the target audience.

It is also important to reemphasize the methodology assumes that the relationship between the percentage of time the target audience travels via mode k does not depend linearly on  $TU_k$  (the total value for TCM "k"). As the disparity between TCMs' total utilities grows, the disparity between their market shares grows exponentially.

## STEP-BY-STEP DIRECTIONS TO CONDUCT PACKAGE ANALYSES

The rest of this chapter is devoted to a step-by-step discussion that describes in detail how to conduct a packaging analysis. The individual steps fall into four broad categories:

- Gathering data
- Identifying TCMs to evaluate as individual measures
- Validating the methodological approach using base case data
- Evaluating overlapping and synergistic measures

## **GATHERING DATA**

### **Collect Travel Data, Establish Base Case Conditions**

- Establish the preexisting conditions in the areas of interest; this includes to what extent TCMs have already been implemented, what AVO (average vehicle occupancy) levels have been achieved during peak and off-peak periods, what types of trips occur in the region, what mode choices have been made in making these trips.
- Determine to what extent travel options are currently available within the region of interest. For example: how widely dispersed are transit services? What are current transit ridership rates? What park and ride lots are available and what percent of their parking spaces are vacant?

## **IDENTIFYING TCMS TO EVALUATE AS INDIVIDUAL MEASURES**

### **Define Target Market for TCMs**

- Define the target market for each individual measure in the package in terms of type of trip targeted (e.g., work trip), type of individual targeted within that trip category (e.g., all service professionals), and the geographic area covered by the TCM (e.g., the CBD of a metropolitan area).

### **Identify Measures That Target Overlapping Audiences**

- Identify areas of overlap: this means identifying which targeted audiences are covered by more than one TCM in a given TCM package.
- For measures that do not overlap, add their effects.
- For measures that do overlap, proceed with remainder of packaging analysis.

### **Characterize Measures By Their Effects**

- Group overlapping measures to distinguish between measures that provide travel options and measures that affect the cost or convenience of trip making. The purpose behind making this distinction is that TCMs that impose new costs on certain types of travel or make some travel modes more or less convenient do not directly provide travel options to potential program participants (options must be

available for behavioral change to occur). Instead, changes in cost or convenience play an important role by altering the environment in which other measures are assessed.

Part of the methodological approach to evaluating packages is to use TCMs that affect travel cost and/or convenience as an indicator for how readily individuals might adopt travel options. The methodology considers measures that influence cost, convenience, reliability, or travel time as measures that may interact synergistically with other TCMs.

- Among the measures that present travel options (e.g., new bus services or rideshare opportunities), separate those that either (1) eliminate trips, or (2) shift the origin or destination (O-D) of trips (i.e., change the geographic placement of where a trip occurs). The purpose behind separating out these measures is to isolate measures that are not likely to interact synergistically. Measures that eliminate or alter the placement of trips (e.g., telecommuting, land use measures) are not as likely to work in combination with other measures designed to (1) promote alternative travel modes (e.g., such as the use of transit) or (2) alter the timing of when a trip occurs (e.g., such as an alternative work schedule).

#### **Analyze Measures That Have Little Overlap**

- Analyze the effects of those measures that either (1) eliminate trips, or (2) shift their O-D; these TCMs will not work well with other TCMs; their effects may be segregated and estimated independent of the other measures (note that this introduces some error in the analysis but offers a way to simplify the methodology).

At this point in the analysis, it should be possible to determine what portion of the overall target market is affected by individual measures that do not overlap, plus determine what portion of the target market is affected by TCMs that eliminate or change the O-D of trips. This portion of the target market should be eliminated from further analysis.

#### **VALIDATING THE METHODOLOGICAL APPROACH USING BASE CASE DATA**

- Identify remaining measures in the TCM package targeting the remainder of the trip making audience, then use multi-attribute analysis to determine the effectiveness of the remaining measures.

- The step-by-step multi-attribute method is a model for evaluating the effectiveness of TCM packages. In order to judge the effectiveness of a package, it is important to first represent existing conditions fairly accurately using the model to validate the model results of the TCM package. This first model simulation can be considered a representation of the "base case," which is carried out by going through the steps of the method using variables that reflect existing conditions. These variables include the values of the different attributes of the modes of travel (i.e., the cost, convenience, travel time, and reliability) and the importance (weights) to the target population of each of these attributes. A set of reasonable variables must be determined that accurately represents the current travel patterns of the target population.
- Once a set of reasonable variables has been found that accurately reflects existing conditions for the base case, a new set of attribute values for each mode of travel can be calculated to reflect the expected changes due to the implementation of a TCM package. These new attribute values together with the importance weights determined for the base case are used in a second simulation. This second simulation is the "control case." A comparison of the control case to the base case will show the effectiveness of the TCM package.
- After having simulated the base case, any number of control scenarios may be conducted. Each control scenario could model the effects of different TCM packages. After simulating these different TCM packages, a side-by-side comparison of their effectiveness can be made.

## **EVALUATING OVERLAPPING AND SYNERGISTIC MEASURES**

### **Conduct "Multi-Attribute Analysis"**

- **Nine-Step Multi-Attribute Method:**

Individuals weigh a number of factors when deciding what trips to make and how to make them. Specific TCMs alter trip-making behavior if the measures affect the factors that people consider in deciding upon the nature and frequency of their trip making. To analyze the effects of a package of measures that overlap target audiences, it is important to understand how each measure (both individually and in concert with other measures) affects the key variables that people weigh. This discussion introduces a methodology to conduct such an analysis. The methodology used is multi-variate, or multi-attribute analysis, and is based on conceptual analytical methodologies described in decision analysis literature (e.g., see Stokey and Zeckhauser, 1978).

**Step 1:** Determine the "attribute profile" for each mode of travel by defining each mode in terms of cost, time, convenience, and reliability.

The major attributes of travel choices can be broken down into four broad categories: (1) cost--including long- and short-term costs; (2) time--including direct travel time enroute plus excess time from the origin and destination to the mode choice; (3) convenience--including comfort, safety, and flexibility of the mode choice; and (4) reliability--focusing on the predictability of the mode choice's ability to reliably deliver the rider to his or her destination. Figure 8-1 illustrates how a mode choice can be described as a function of these attributes; the figure also describes units of measure for each attribute.

**Step 2:** For a given trip type (work or non-work trips) determine the best and worst limits of the attribute profile; i.e., determine the best and worst cost, convenience, travel time, and reliability that are possible in the region being analyzed for the TCM package.

For example, the worst cost could be 85 cents per mile, and the best possible cost could be 20 cents per mile. The best possible convenience could be immediate access, and the worst possible convenience could be only trip-end access.

**Step 3:** Determine the cost, convenience, travel time, and reliability associated with each mode of travel; then scale each mode's relative cost, convenience, travel time, and reliability on the "best to worst" scale for that trip type; Figure 8-2 provides an example. This will likely have to be done for at least two different categories: work and non-work trips.

The convenience and reliability of a mode of travel must be given a value between 0 and 1, where 0 is the worst possible value and 1 is the best possible value. Travel time and cost values may be calculated directly as follows:

$$\text{COSTVAL}_k = (\text{worst cost} - \text{COST}_k) / (\text{worst cost} - \text{best cost}) \quad (8-3)$$

$$\text{TIMEVAL}_k = (\text{worst time} - \text{TIME}_k) / (\text{worst time} - \text{best time}) \quad (8-4)$$

where

- $k$  = the travel mode (if there are 3 modes being analyzed, then  $k$  will range from 1 to 3),
- $\text{COST}_k$  = the cost of travel of mode  $k$ ,
- $\text{TIME}_k$  = the travel time of mode  $k$ ,
- $\text{COSTVAL}_k$  = the cost value of mode  $k$ , and
- $\text{TIMEVAL}_k$  = the time value of mode  $k$ .

Figure 8-3 provides an example of these "value functions." The equations presented in

this step of the method are linear calculations of the attribute value between the best and worst limits. These equations are simple mathematical approximations to the actual values, which may not depend linearly on the limits. For example, 5 additional minutes added to a 10-minute trip might not make that much difference to the trip maker; however, 5 minutes added to a 50-minute trip might represent a significant loss in utility for the trip maker due to the length of the original trip. In light of this potential nonlinearity in determining the value function, one should view these equations as mathematical approximations that provide guidance in determining the values.

**Step 4:** Determine sets of weight profiles,  $(\lambda_{\text{cost}}, \lambda_{\text{convenience}}, \lambda_{\text{time}}, \lambda_{\text{reliability}})$ , for the population in the region. Each set of  $\lambda$ 's should represent the importance of the cost, convenience, time, and reliability of a significant portion of the population in the region. The  $\lambda$ 's are assigned the percentage of importance of each of the attributes, so they must sum up to 1.

Among the range of important considerations determining mode choice identified in other behavioral studies are the following:

There is a strong correlation between commute distance and mode choice. Long distance commuters have higher ride sharing rates than those with shorter commutes (Crain, 1984; DOT, 1985).

A main problem cited by solo commuters is the length of time necessary to take the bus to work. In most cases, those surveyed could drive to work in a fraction of the time it would take to ride transit. Another common perception is that bus service may be unreliable (Crain, 1984; DOT, 1984).

Some commuters, especially women, feel that their personal safety is at risk while waiting at, or walking to, bus stops, especially in the dark (Crain, 1984).

Childcare issues also can affect commuter mode choice. Many individuals cite the need to respond to child health emergencies and childcare needs as reasons for driving to work rather than taking transit. Many non-work-related trips during the day are generated by parents shuttling children to daycare, doctors' appointments, and other commitments. This trend is more prevalent with women in the work force than men (Crain, 1984; Raux et al., 1986; DOT, 1985).

A major deterrent to carpooling is incompatibility of people's schedules. Childcare issues also serve to deter potential ridesharing (people want to be able to respond to emergencies if necessary) (Crain, 1984; DOT, 1984).

Part-time carpooling is viewed more positively than regular (i.e., daily) carpooling. In one study, one group expressed a willingness to rideshare on a part-time basis, for example 2 or 3 times per week. The other days they either

have specific obligations that require car availability or they simply wish to have their car for the freedom it offers.

Commuters often underestimate or are not aware of their true commute costs. For example, one woman estimated her commute costs, including insurance, gas, maintenance, etc. to be around 4 cents per mile. In actuality, the total cost was around 18 cents per mile (DOT, 1985).

Some factors considered by people when deciding whether or not to rideshare or take transit involve the other individuals they would travel with. Personal characteristics such as smoking can either encourage or discourage potential ridesharers, depending upon their feelings about these habits (Crain, 1984; DOT, 1984).

The perceived difficulty in deciphering bus and other transit schedules can deter inexperienced transit users and make them less likely to consider transit as a viable alternative to driving (Crain, 1984).

To summarize using an example, based on the mode choice literature, a reasonable weighting of each attribute's importance for work trips might be: 0.4 for cost, 0.3 for travel time, 0.2 for convenience, and 0.1 for reliability (summing to 1.0). Methodology users are encouraged to select weights appropriate to their specific areas and trip types.

**Step 5:** Calculate the total utilities of each mode of travel. Total utility will reflect the relative weight of each attribute (from step 4), and each measure's "value function" for that attribute (from step 3). See Figure 8-4.

The calculation of the total utility for a particular travel mode,  $k$ , and weight profile,  $(\lambda_1, \lambda_2, \lambda_3, \lambda_4)$ , is:

$$TU_k = \text{COSTVAL}_k * \lambda_1 + \text{CONVVAL}_k * \lambda_2 + \text{TIMEVAL}_k * \lambda_3 + \text{RELIVAL}_k * \lambda_4 \quad (8-5)$$

where

$TU_k$	=	the total utility of mode $k$ ,
$\text{COSTVAL}_k$	=	the cost value of mode $k$ ,
$\text{CONVVAL}_k$	=	the convenience value of mode $k$ ,
$\text{TIMEVAL}_k$	=	the time value of mode $k$ ,
$\text{RELIVAL}_k$	=	the reliability value of mode $k$ ,
$\lambda_1$	=	the importance of the cost,
$\lambda_2$	=	the importance of the convenience,
$\lambda_3$	=	the importance of the time, and
$\lambda_4$	=	the importance of the reliability.

**Step 6:** Calculate the estimated percentage of time a person from the target population group with weight profile  $(\lambda_1, \lambda_2, \lambda_3, \lambda_4)$  will travel via mode k relative to the travel modes considered.

Presented is a mathematical representation of how to estimate the percent of time the target audience utilizes the individual travel modes. Suppose there are N different modes of travel that are being considered to be part of the TCM package (for example, N might be 3, representing transit, rideshare, and telecommuting). For each person, there is a set of values  $TU_k$  for  $k = 1$  through N, where  $TU_k$  represents the total utility of TCM "k." The percentage of time that a person will travel using mode k will depend upon the TU of k in relation to the TU of their remaining mode choice options. For example, if a person has a total mode utility value of 0.9 for single occupant travel and only 0.1 for public transit, then it is unlikely that this person will travel on public transit (given two options, people will almost never buy a product of clearly inferior value.) However, if a person has a TU of 0.41 for single occupant travel and 0.40 for public transit, then it is probable that this person will take public transit nearly the same amount of time he or she rides in a single occupant vehicle. In precise terms, the packaging methodology must consider that the percentage of time a person will travel via mode k is dependent upon the differences in magnitude between  $TU_k$  and all the other TU numbers for that person.

When extending a travel mode's total utility to an entire target market of trip makers, the total utility serves as a surrogate for the degree to which a specific measure will be utilized. To relate total utility to percent of time a TCM is utilized, it is important to represent that measures of little value are not likely to be utilized, while measures of greater value are likely to be substantially utilized. As a concrete example, consider one of the packages just discussed: a person has a total mode utility value of 0.9 for single occupant travel and only 0.1 for public transit. With such a large disparity in utility between these two travel options, it is unlikely that transit will be utilized. It is therefore inappropriate to linearly relate target market for a TCM to its total utility (i.e., in this example, it is unlikely that 10 percent of the target market would utilize transit). A better mathematical approach relating total utility to target market use of a TCM is to relate the percent of time that the target audience will utilize a given TCM as a function of the square of the utility of that mode choice. Mathematically, using the square of the utility accentuates the differences between measures that have widely different utilities, while maintaining a closer balance between measures that have similar utilities.

Equation 8-6 illustrates how to calculate percentages of mode travel for a person with TU values  $TU_1$  through  $TU_N$ :

$$P_k = TU_k^2 / (\sum_{j=1, N} TU_j^2) \quad (8-6)$$

where

$P_k$  = percentage of time this person (or target group of trip makers) will travel via mode k relative to the N modes examined.



It is important to note the methodology assumes that the relationship between the percentage of time a person travels via mode  $k$  does not depend linearly on  $TU_k$ . It is also important to note that this formulation assumes that "N" captures all of the travel modes under consideration by the target audience.

**Step 7:** Determine the number of people that will travel via mode  $k$ .

Multiply the percentage of time a target audience uses mode " $k$ " (the  $P_k$ 's calculated in step 6) by the number of people in the group represented by the weight profile  $(\lambda_1, \lambda_2, \lambda_3, \lambda_4)$ . This represents the percentage of time that people from the target group will travel via mode  $k$ .

**Step 8:** Determine the new mode values (i.e., cost, time, convenience, and reliability) that reflect the implementation of a TCM package. With these new values and the weight profile determined from the base case, repeat steps 3-7 above to determine the new percentages of time people will travel via the different  $N$  modes of travel. The new percentages are the results of the "control case," and the old percentages are the results of the "base case."

**Step 9:** Compare the differences in the percentage of time that people will travel via mode  $k$  from before and after the implementation of a TCM package. This is the difference between the control case and the base case, which reveals the effectiveness of the TCM package.

## **EXAMPLE APPLICATION OF PACKAGING METHODOLOGY**

### **Validation of Packaging Methodology**

The first task in applying this methodology involves validation of base-case values using "real world" data. Using modal split information for work trips as our target values (MTC, 1991), a simple spreadsheet is constructed to calculate total utility and percent use using the formulas presented in Chapter 8. This spreadsheet enables the user to immediately evaluate the impact of altering attribute values on the total value and percentage use of each TCM.

Values are manipulated until the calculated percent use approximates actual percentages for the region of interest. Tables 8-1a and 8-1b show the results of a sample initial analysis using data for the San Francisco Bay Area (MTC, 1991).

TABLE 8-1a. Methodology validation using "real world" data.

TRAVEL MODE	COST (0.25)	CONVENIENCE (0.45)	TIME (0.20)	RELIABILITY (0.1)	TOTAL UTILITY (1.0)
SOV (Base)	0.5	0.9	0.75	0.9	0.77
Transit	0.5	0.2	0.25	0.2	0.30
Rideshare	0.7	0.2	0.55	0.3	0.40
*Telecommuting	0	0	0	0	0
*Flextime	0	0	0	0	0
*SOV w/ Parking	0	0	0	0	0

\* Note that these measures are part of the example TCM package and are not included when calculating base case values for the San Francisco Bay Area.

TABLE 8-1b.

TRAVEL MODE	CALCULATED USE (in percent)	ACTUAL MTC VALUE
SOV Base Case	71 %	71.4 %
Transit	10 %	10.7 %
Ridesharing	19 %	17.9 %
Telecommuting	0	NA
Flextime	0	NA
SOV w/ Parking Management	0	NA
TOTAL	100 %	100 %

These tables can now be used as a guide for determining attributes of implemented TCMs.

### Application of Packaging Methodology

After the methodology has been validated using "real world" data, the next task is to apply it for the measures to be included in the TCM package. Our example package includes ridesharing, transit, telecommuting, flextime, and a parking management program primarily directed at single occupant vehicles. Using the validation values for ridesharing and transit as a guide, the original spreadsheet is altered to include the value functions of the travel options after implementation. In our example, the SOV mode

without a parking management program is considered a non-option, forcing these trips to be taken via other modes. Tables 8-2a and 8-2b show the results of this application. Note that the value functions for transit and ridesharing remain approximately the same as before program implementation. Slight increases in convenience and time values for ridesharing have been made to reflect the nature of the proposed parking management program, which allows convenient, no-cost parking for carpools.

TABLE 8-2a. Methodology application to example TCM package.

TRAVEL MODE	COST (0.25)	CONVENIENCE (0.45)	TIME (0.20)	RELIABILITY (0.1)	TOTAL UTILITY (1.0)
*SOV (Base)	0.0	0.0	0.0	0.0	0.0
Transit	0.75	0.20	0.25	0.30	0.35
Rideshare	0.85	0.20	0.55	0.20	0.44
Telecommute	0.40	0.90	0.75	0.90	0.75
Flextime	0.10	0.90	0.80	0.80	0.66
SOV w/ Parking	0.00	0.85	0.70	0.80	0.59

\* Note that this measure is assumed to be a non-option for this example TCM package.

The new modal splits after implementation of the TCM package are shown in Table 8-2b.

TABLE 8-2b.

Package TCM	Calculated Use (in percent)
SOV Base Case	NA
Transit	7.6
Rideshare	11.1
Telecommute	33.9
Flextime	26.7
SOV w/ Parking Management	21.6
TOTAL	100

By assuming that the SOV mode without a parking management program will be made unavailable to the target population, trips previously made via this mode are shifted to other TCM options. Original mode shares for transit and ridesharing can be seen to

decrease between the validation and the example application, reflecting the redistribution of work trips as a result of a greater number of commute options. After implementation, telecommuting becomes the most desirable commute alternative, largely because of its high level of convenience and time saving features.

## GLOSSARY OF VARIABLES

<b>AFF</b>	Number of individuals potentially affected by parking management program
<b>AFF<sub>e</sub></b>	Affected employees who do not use spillover parking when subject to a parking management program
<b>AVO</b>	Average vehicle occupancy
<b>AVO<sub>n</sub></b>	Average vehicle occupancy for non-work trips
<b>BASE</b>	Base price of parking spaces prior to parking management program
<b>C<sub>0</sub></b>	Commute costs (per week) prior to telecommuting (or participation in another TCM)
<b>C<sub>1</sub></b>	Commute costs (per week) after beginning participation in a TCM program
<b>CARP</b>	Number of new carpoolers attracted by TCM implementation
<b>CIRC</b>	Average round-trip distance to park and ride lots from freeway and/or from freeway to other ridesharer's homes
<b>CONVVAL<sub>k</sub></b>	Convenience value of mode k
<b>COST<sub>b</sub></b>	Base out-of-pocket costs for work trips prior to parking management program
<b>COSTVAL<sub>k</sub></b>	Cost value of mode k
<b>COST<sub>k</sub></b>	Cost of travel of mode k

$D$	Frequency of work (days per week)
$\delta$	Percent of workforce participating in alternative work schedules program
$D_j$	Distance between intersections $j$ and $j + 1$
$\Delta VMT_h$	Decreased VMT resulting from decrease in work trips due to ridesharing
$\Delta VMT_n$	VMT changes due to changes (generally increases) in non-work trips
$\Delta VMT_p$	Change in VMT during peak period
$\Delta VMT_{pe}$	Decreased VMT for ridesharers who drive to park and ride lots and join existing carpools
$\Delta VMT_{pn}$	Decreased VMT for ridesharers who drive to park and ride lots and form new carpools
$\Delta VMT_w$	Total VMT savings resulting from changes in work trips
$\Delta VMT_x$	Extra VMT associated with picking up other ridesharers
$DRVAGE$	Percent of population that is of driving age
$\epsilon_m$	Elasticity of mode choice with respect to cost
$\epsilon_s$	Elasticity of peak speed with respect to volume
$EMPL$	Percent of population that is employed
$F_r$	Frequency of ridesharing (days per week)
$F_t$	Frequency of telecommuting (days per week)
$G_{early}(t)$	Distribution of vehicle trips affected by alternative work schedule program that will occur mostly before the peak period
$G_{late}(t)$	Distribution of vehicle trips affected by the alternative work schedule program that will occur mostly after the peak period

$G(t)_{old}$	Distribution of peak period travel prior to implementation of alternative work schedule program
$h(t)$	Distribution of non-work trips during peak periods
<b>HSULD</b>	Average household size (number of people)
$I_{Cap}$	Percentage increase in capacity
<b>INCRS</b>	Percent increase in parking prices from parking management program
$k$	Travel mode
$k_{jam}$	Traffic density at jam density
$k_{new}$	New density of traffic after addition of a lane
$k_{old}$	Old density of traffic before addition of a lane
$\lambda_1$	Importance of cost (also $\lambda_{cost}$ )
$\lambda_2$	Importance of convenience (also $\lambda_{convenience}$ )
$\lambda_3$	Importance of time (also $\lambda_{time}$ )
$\lambda_4$	Importance of reliability (also $\lambda_{reliability}$ )
<b>LOTDIST</b>	Average distance to park and ride lots (round trip)
<b>M</b>	Total vehicle trips per day in the study region (used in alternative work schedules methodology)
<b>M</b>	Total number of intersections (in traffic signalization methodology) (also referred to as the number of links between retimed lights)
$M_{non}$	Number of non-work trips per day (used in alternative work schedule methodology)
$M_{work}$	Number of work trips made per day (used in alternative work schedule methodology)
<b>MODE</b>	Number of individuals shifting from SOV to other modes due to parking management program

<b>MODE<sub>r</sub></b>	Individuals in parking management program who shift to ridesharing
<b>MODE<sub>re</sub></b>	Individuals in parking management program who begin ridesharing and join existing carpools
<b>MODE<sub>rn</sub></b>	Individuals in parking management program who begin ridesharing and form new carpools
<b>MODE<sub>t</sub></b>	Individuals in parking management program who shift to transit
<b>MODE<sub>w</sub></b>	Individuals in parking management program who shift to walking or bicycling
<b><math>\mu</math></b>	Mean hour of peak period (e.g., if peak period is from 7 to 9, $\mu$ is 8).
<b><math>\mu_1</math></b>	Mean hour of travel for early flex-time travellers
<b><math>\mu_2</math></b>	Mean hour of travel for late flex-time travellers
<b>N<sub>j,car</sub></b>	Number of vehicles that travel over the new road between intersections $j$ and $j + 1$
<b>N<sub>lane</sub></b>	Number of lanes in the direction of flow before a lane is added
<b>N(t)</b>	Distribution of work trips during the morning peak period
<b>N<sub>shift</sub></b>	Number of trips that can potentially be shifted to off-peak periods as a result of an alternative work schedule program
<b>NCAR</b>	Average number of people per carpool (including vanpools)
<b>NEW</b>	New price of employee parking spaces
<b>NOCAR</b>	Percent of population that does not own a car
<b>NONWRK<sub>h</sub></b>	SOV Non-work trip increases by household members of ridesharers
<b>NONWRK<sub>t</sub></b>	Average daily increase in non-work SOV trips made by telecommuters
<b>NONDIST</b>	Average distance of non-work trips (one-way)
<b>NONWRK<sub>i</sub></b>	Total increase in non-work vehicle trips



<b>NONWRK<sub>h</sub></b>	Increase in non-work trips by members of the TCM participant's household
<b>NONWRK<sub>t</sub></b>	Average daily change in non-work trips for telecommuters
<b>NOSOV</b>	Percent of work trips made by non-SOV modes
<b>NSPC</b>	Number of parking spaces whose prices have been raised due to parking management program
<b>P<sub>e</sub></b>	Percent of carpoolers who join existing carpools and do not drive to park and ride lots
<b>P<sub>h</sub></b>	Percent of transit users or ridesharers who leave their vehicles at home
<b>P<sub>jk</sub></b>	Percent of trips made at hour j that move to hour k for all hours for which there is a percentage shift.
<b>P<sub>speed</sub></b>	Percentage increase in speed due to traffic signalization
<b>P<sub>stop</sub></b>	Percentage decrease in average number of stops
<b>PCT<sub>op</sub></b>	Percent of the total work force represented by employees moving their work travel from peak to off-peak periods in response to a staggered work hours program
<b>PCT<sub>pn</sub></b>	Percent of non-work travel occurring in the peak period
<b>PCT<sub>pw</sub></b>	Percent of work travel occurring in the peak period
<b>P<sub>k</sub></b>	Percentage of time individual (or target group) will travel via mode k
<b>P<sub>n</sub></b>	Percent of telecommuters who work from home rather than from satellite work centers
<b>P<sub>n</sub></b>	Percent of carpoolers who form new carpools and do not drive to park and ride lots
<b>P<sub>pe</sub></b>	Percent of ridesharers who drive to park and ride lots who also join existing carpools

$P_{pn}$	Percent of ridesharers who drive to park and ride lots and who form new carpools
$PN_{pk}$	Percent of non-work trips made during the peak period (used for alternative work schedule methodology)
$PW_{pk}$	Percent of work travel that occurs during the peak period (definition used in alternative work schedules methodology)
$RELIVAL_k$	Reliability value of mode k
$SATDIST$	Average distance to satellite work centers
$\sigma$	Standard deviation of when vehicle trips occur (used in alternative work schedule methodology)
$\sigma_1$	Standard deviation of the hour of travel for early flextime travellers
$\sigma_2$	Standard deviation of the hour of travel for late flextime travellers
$SPD_p$	Change in peak period speeds (percent)
$SPILL$	Number of spillover spaces available to employees subject to a parking management program
$STG_{pk}$	Number of employees whose new start and end times move them from a peak to an off-peak period under a staggered work hours program
$t_{end}$	Ending time of the peak period
$t_{endnew}$	Latest time for alternative work schedule participants to travel to work
$t_{saved}$	Travel time a person will save due to addition of a lane on a freeway or due to traffic signal re-timing
$t_{start}$	Beginning time of the peak period
$t_{startnew}$	Earliest time alternative work schedule participants travel to work
$t_{stop}$	Average time spent stopped at intersections

$t_{total}$	Total travel time (used in traffic signalization methodology)
TEL	Number of new telecommuters attracted by the TCM
$TEL_s$	Number of telecommuters who work from satellite work centers (new telecommuters attracted by the TCM program)
$TIME_k$	Travel time of mode k
$TIMEVAL_k$	Time value of mode k
$TRIPGEN_n$	Average number of non-work SOV trips demanded per person per day (for persons owning vehicles)
$TRIPGEN_w$	Average number of SOV work trips demanded per person per day
$TRPR_t$	Total trip change caused by telecommuting
$TU_k$	Total utility of mode k
$u_{cap}$	Average vehicle speed at capacity of freeway or roadway
$u_{free}$	Free-flow speed
$u_j$	Mean speed between intersections j and j+1
$u_{j,new}$	The average speed of vehicle between stops after a new lane is added
$u_{j,old}$	The average speed of vehicle between stops before a new lane is added
$u_{maxcap}$	Speed at maximum freeway capacity
UNEMPL	Percent of population that is unemployed
$VEH_{op}$	Number of vehicle trips moved out of the peak period by a staggered work hours program
$VMT_n$	Total non-work trip VMT
$VMT_w$	Total work trip VMT
$w(t)$	Distribution of work trips during peak periods

$w(t_j)$	Distribution of work trips at hour j
$w_{new}(t_j)$	New distribution of work trips at hour j
$WRKDIST_a$	Average one-way trip distance for work trips
$WRKDIST_r$	Average one-way work trip distance for ridesharers (tends to be somewhat longer than for non-ridesharers)
$WRKTRP_b$	Basic vehicle work trip reduction due to telecommuting
$WRKTRP_e$	Number of vehicle work trips eliminated by carpoolers joining existing carpools (average number per day)
$WRKTRP_{ih}$	Number of vehicle work trips increased by members of ridesharers' or telecommuters' households who switch from shared modes (transit or carpools) to SOVs due to increased availability of vehicle
$WRKTRP_h$	Work trips reduced by employees subject to parking management program who begin sharing rides to work (either transit or ridesharing) who leave their vehicles at home
$WRKTRP_m$	Extra SOV work trips made by telecommuters switching from shared modes to SOV modes
$WRKTRP_n$	Number of vehicle work trips eliminated by carpoolers forming new carpools (average number per day)
$WRKTRP_r$	Total vehicle work trip reduction due to ridesharing program
$WRKTRP_t$	Total vehicle work trip reductions due to telecommuting
Y	Number of employees travelling to work in a vehicle

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Appendix A

**RECURSIVE EFFECTS OF TCMs**



## Appendix A

### RECURSIVE EFFECTS OF TCMs

Trip reductions realized from a TCM program may result in decreased congestion which may result in some increase in SOV use by non-SOV commuters such as transit riders. This extra SOV travel can be estimated using the elasticity of mode choice with respect to cost:

$$WRKTRP_i = \epsilon_m \times (C_0 - C_1)/C_0 \times NOSOV_w \times TEL \times F/D$$

where

$WRKTRP_i$	=	Extra SOV work trips taken by telecommuters due to mode switching
$\epsilon_m$	=	Elasticity of mode choice with respect to cost
$C_0$	=	Pre-telecommuting travel time costs (average per day)
$C_1$	=	Post-telecommuting travel time costs (average per day)
$NOSOV_w$	=	Percent of work trips that use non-SOV travel modes for work travel trips

As with ridesharing, this treatment is a one-step feedback loop to consider that the benefits from trip reduction will tend to be offset somewhat by latent demand for SOV use. The equation cannot be used until the base trip change is used to calculate speed changes.



## Appendix B

### **RELATIONSHIP OF VEHICLE DENSITY TO SPEED**





## Appendix B

### RELATIONSHIP OF VEHICLE DENSITY TO SPEED

This appendix discusses mathematical relationships between vehicle densities and travel speed. To begin the discussion, it is necessary that a few variables be defined. Let

k	=	density (number of vehicles per mile of road, in vehicles/mile)
v	=	volume (number of vehicles per hour passing over a section of road, in vehicles/hour)
u	=	average speed of the vehicles (in miles/hour)

The relationship of these three variables is:

$$v = uk.$$

Field data has been collected on average vehicle speeds for different vehicle densities. The empirical curve of the average speeds at different densities shows that speeds decrease as the density increases. This empirical curve is nearly linear in the middle, i.e. when the vehicle density is not close to "jam" density (vehicle density at traffic jam conditions, or the maximum possible density) or when the vehicle density is not close to zero. When the vehicle density is less than a minimum density, the average speed of vehicles does not continue to increase as density decreases; instead it remains fairly constant when the density is less than this minimum density. This can be explained by the limitations imposed by speed limits and by the limitations on the vehicles themselves, which may not be able to travel at speeds higher than some maximum. At the other extreme, when the vehicle densities are great, the speed is near zero, and the speed decreases more slowly than the slope in the middle of the empirical curve. The mean vehicle speed is then zero when the density is equal to jam density.

One approach to relate density to average vehicle speed is to consider the relationship to be linear, which is appropriate when the vehicle density is far from zero and far from jam density. An example of such a relationship is put forward by Greenshields (B.D. Greenshields. "A Study of Traffic Capacity," Proc. Highw. Res. Bd., 14, 448-477 (1935), in ITE, 1982); it is

$$u = u_{\text{free}}(1 - k/k_{\text{jam}})$$

where

$u_{\text{free}}$  = free flow speed

$k_{\text{jam}}$  = jam density.

The free flow speed is the maximum speed at which one could drive on a road assuming there were no other vehicles on the road; it is probably near 65 mph on a straight freeway. The jam density is the density of vehicles under traffic jam conditions. This is about 250 vehicles per mile (in one lane).

A second model of the average vehicle speed in terms of the vehicle density is a logarithmic relationship (see, (H. Greenberg. "An Analysis of Traffic Flow," Oper. Res., 7(1), 79-85 (1959), in ITE, 1982). This relationship is a closer approximation to empirical data than the linear model when densities are close to jam density. The relationship is:

$$u = u_{\text{cap}} \ln(k_{\text{jam}}/k)$$

where  $\ln$  is the natural log and

$$u_{\text{cap}} = \text{average vehicle speed at capacity } (\approx u_{\text{free}}/2).$$

In order to understand what the speed is at capacity, one must first understand what capacity is. The capacity of a road is defined to be the maximum number of vehicles that can feasibly pass over the road per hour; i.e., it is the maximum volume. Capacity is a constant that reflects the characteristics of a particular roadway in one direction of flow. Contrary to an individual driver's perceptions, a road is being used "efficiently" from an engineering viewpoint when the volume is near the capacity.

As the volume approaches capacity, the speed of traffic will be less than the maximum allowable speed, the free flow speed,  $u_f$ . In fact, when the volume equals capacity, the speed,  $u$ , is about  $u_f/2$ . This number can be obtained by substituting the relationship

$$k = v/u$$

into the linear model, and then solving for  $v$ . One gets the equation

$$v = uk_j - u^2(k_j/u_f).$$

Then the maximum volume occurs when

$$u = u_f/2.$$

Recall that the logarithmic model is considered to be more accurate than the linear model when the density of cars is close to jam density. The linear model is considered to be accurate when vehicle densities are far from jam density and zero (ITE, 1982).



Appendix C

**EXAMPLE ELASTICITIES DERIVED FROM  
TRANSPORTATION MODELING**

Source: Working Paper. Screening of Transportation Control Measures for the San Francisco Bay Area, by Greig Harvey, November 17, 1989.

**Table 1: Demand Elasticities with Respect to In-vehicle Travel Time**

Base in-vehicle time (minutes)	Base Mode Share								
	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
10	-0.22	-0.19	-0.17	-0.14	-0.12	-0.10	-0.07	-0.05	-0.02
20	-0.43	-0.38	-0.34	-0.29	-0.24	-0.19	-0.14	-0.10	-0.05
30	-0.65	-0.58	-0.50	-0.43	-0.36	-0.29	-0.22	-0.14	-0.07
40	-0.87	-0.77	-0.67	-0.58	-0.48	-0.38	-0.29	-0.19	-0.10
50	-1.08	-0.96	-0.84	-0.72	-0.60	-0.48	-0.36	-0.24	-0.12
60	-1.30	-1.15	-1.01	-0.87	-0.72	-0.58	-0.43	-0.29	-0.14
70	-1.51	-1.35	-1.18	-1.01	-0.84	-0.67	-0.50	-0.34	-0.17
80	-1.73	-1.54	-1.35	-1.15	-0.96	-0.77	-0.58	-0.38	-0.19

**Table 2: Demand Elasticities with Respect to Travel Cost**

Base travel cost (cents)	Base Mode Share								
	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
50	-0.16	-0.14	-0.12	-0.10	-0.09	-0.07	-0.05	-0.03	-0.02
100	-0.31	-0.28	-0.24	-0.21	-0.17	-0.14	-0.10	-0.07	-0.03
150	-0.47	-0.42	-0.37	-0.31	-0.26	-0.21	-0.16	-0.10	-0.05
200	-0.63	-0.56	-0.49	-0.42	-0.35	-0.28	-0.21	-0.14	-0.07
250	-0.78	-0.70	-0.61	-0.52	-0.43	-0.35	-0.26	-0.17	-0.09
300	-0.94	-0.83	-0.73	-0.63	-0.52	-0.42	-0.31	-0.21	-0.10
350	-1.10	-0.97	-0.85	-0.73	-0.61	-0.49	-0.37	-0.24	-0.12
400	-1.25	-1.11	-0.97	-0.83	-0.70	-0.56	-0.42	-0.28	-0.14
450	-1.41	-1.25	-1.10	-0.94	-0.78	-0.63	-0.47	-0.31	-0.16
500	-1.57	-1.39	-1.22	-1.04	-0.87	-0.70	-0.52	-0.35	-0.17

**Table 3: Demand Elasticities with Respect to Out-of-vehicle Travel Time**

Base out-of vehicle time	Base Mode Share								
	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
5	-0.24	-0.22	-0.19	-0.16	-0.14	-0.11	-0.08	-0.05	-0.03
10	-0.49	-0.43	-0.38	-0.33	-0.27	-0.22	-0.16	-0.11	-0.05
15	-0.73	-0.65	-0.57	-0.49	-0.41	-0.33	-0.24	-0.16	-0.08
20	-0.98	-0.87	-0.76	-0.65	-0.54	-0.43	-0.33	-0.22	-0.11
25	-1.22	-1.09	-0.95	-0.81	-0.68	-0.54	-0.41	-0.27	-0.14
30	-1.47	-1.30	-1.14	-0.98	-0.81	-0.65	-0.49	-0.33	-0.16
35	-1.71	-1.52	-1.33	-1.14	-0.95	-0.76	-0.57	-0.38	-0.19
40	-1.96	-1.74	-1.52	-1.30	-1.09	-0.87	-0.65	-0.43	-0.22

## Appendix D

### **INCORPORATION OF TCM CHANGES INTO DTIM AND BURDEN**





## Appendix D

### INCORPORATION OF TCM CHANGES INTO DTIM AND BURDEN

#### OVERVIEW

The TCM evaluation methodologies developed in earlier chapters result in estimates of:

- net change in trips
- net change in VMT
- percent change in speed.

For certain TCMs, information on trip type affected or time of day in which changes in travel activity occur will also result from the analysis. This information can be used in a general manner to assess the relative benefits of TCM measures, but a better analysis of the potential air quality effects of a TCM or package of TCMs is obtained if these net changes in travel activity are combined with vehicle emission factors. This results in calculation of net effects on regional emissions associated with introduction of TCMs. Alternatively, one can calculate baseline vehicle emission inventories for a region, without implementation of any TCMs, and subsequently calculate vehicle emission inventories which are representative of vehicle activity patterns after implementation of TCMs. This approach provides a context in which to assess overall TCM effects upon regional emissions. Regional emission inventories can subsequently be used as input to air quality models, such as OZIPM or UAM, which allow one to make a determination as to the regional air quality effects of a particular TCM or TCM package.

The ARB has developed two computer models which are used to develop regional vehicle emission inventories. The first of these which we will discuss is known as BURDEN. There are currently two versions of this model available; the first, BURDEN7C, is used to develop current year vehicle emission inventories; the second, T2BURDEN, is used to develop planning inventories for future years. This discussion will focus on the version BURDEN7C<sup>1</sup>. The second ARB model which will be discussed was developed by CALTRANS, and is known as DTIM<sup>2</sup>. DTIM is currently being updated by CALTRANS.

## MODELING TCM EFFECTS WITH BURDEN

BURDEN7C provides the user with county (and air basin) level annual average emission estimates of vehicle emissions by vehicle class and operating mode. Input to the model are county level vehicle activity estimates (VMT, vehicles, trips, and speed), emission factors from EMFAC, and various other parameters unlikely to be affected by TCMs. None of these input parameters are differentiated by time of day or trip type.

The methods described below will allow emissions modeling of the effects of most types of TCMs except those, such as vehicle scrappage programs, which effect fleet characteristics, i.e., distribution of vehicles by model year and vehicle class. TCMs which affect fleet characteristics must be modelled through manipulation of the inputs to the EMFAC and/or CALIMFAC programs; it is recommended that the ARB be consulted when calculating emissions changes for such measures. The remaining discussion is applicable only to those TCMs which are not intended to alter regional fleet characteristics.

To model effects of TCMs with BURDEN, information on the net change in VMT and trips must be calculated. One of the data files input to the BURDEN program contains calendar year specific estimates of VMT, vehicles, and trips for each vehicle class within each county. The information in this file should be modified for the county of interest as follows:

$$\begin{aligned} \text{TRIP}_{\text{new}} &= \text{TRIP}_{\text{old}} + \text{TRIP}_r \\ \text{VMT}_{\text{new}} &= \text{VMT}_{\text{old}} + \text{VMT}_r \end{aligned}$$

where

$\text{TRIP}_{\text{new}}$  is the number of trips made by a specific vehicle class after implementation of TCM(s);

$\text{TRIP}_{\text{old}}$  is the number of trips made by a specific vehicle class taken from input files to BURDEN;

$\text{TRIP}_r$  is the calculated number of trips either increased or reduced through implementation of TCM(s), which can be either positive or negative;

$\text{VMT}_{\text{new}}$  is the VMT of a specific vehicle class after implementation of TCM(s);

$\text{VMT}_{\text{old}}$  is the VMT of a specific vehicle class taken from input files to BURDEN;

$\text{VMT}_r$  is the calculated change in VMT through implementation of TCM(s), which can be either positive or negative.

Another file input to BURDEN contains the fraction of total county level VMT accumulated in distinct speed ranges for specified calendar years for each county in California. Calculated percent changes in either peak or off-peak vehicle speeds which result from TCM implementation must be used to redistribute total county level VMT among the distinct speed ranges input to BURDEN. Some engineering judgement must be relied upon to accomplish this, since there is no differentiation in the BURDEN inputs as to how much of total VMT is assumed to have been accumulated in the peak and off-peak periods, nor as to what average peak and off-peak speeds are. Calculated TCM effects on peak and off-peak speed can be combined for an average daily TCM percent change in vehicle speed, by calculating a linear weighted average with peak and off-peak VMT.

The county level average speed can be calculated from the speed distribution input to BURDEN. The average daily calculated percent change in speed, after implementation of a TCM or TCM package, is applied to the county level average speed to calculate a new county level average speed. Unfortunately, the redistribution of total VMT among all the speed ranges in order to be consistent with this new average daily speed is a multivariate problem without enough equations to be solved, which requires that a simplified approach to redistributing speeds be developed. This design of this approach should be influenced by the characteristics of the TCM(s) modeled, but is primarily a matter of engineering judgement.

## **MODELING TCM EFFECTS WITH DTIM**

DTIM is a software tool developed by CALTRANS and used by the ARB to create hourly, gridded motor vehicle emission inventories for a specific air quality episode day and modeling region. It requires link and traffic analysis zone-specific speeds, travel time, distances and travel volumes, such as are obtained from transportation models. It also uses emission factors, expressed as grams per hour or per trip, obtained from EMFAC. Various other parameters are input to the program, but the effects of TCMs upon these parameters, in particular the hourly distribution of vehicle activity, cannot be evaluated through the TCM calculations described above.

To model TCM emission effects with DTIM, information on the percent change in VMT and trips must be calculated through the methodology outlined above. Information on VMT changes must also be expressed as changes in vehicle hours travelled (VHT). These percent changes, as well as percent changes in vehicle speed (either peak/off-peak or average daily) are applied as factors to the transportation model outputs which are input in a format referred to as "freeway files" to the DTIM model, in essence creating a new set of these files which represent travel activity with implementation of TCM measures. Since the format of these "freeway files" differs according to the version of DTIM employed, anyone using this methodology should consult with CALTRANS to determine the exact format of files input to DTIM.

The DTIM model is then run with both the original set of travel activity information as well as with the new set of files which represent TCM implementation. From the two hourly, gridded emission files produced from these model exercises, the emission effects of a TCM or TCM package can be evaluated.

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